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Behavioral State Classification in Epileptic Brain using Intracranial Electrophysiology

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Abstract

Objective—Automated behavioral state classification can benefit next generation implantable epilepsy devices. In this study we explored the feasibility of automated awake (AW) and slow wave sleep (SWS) classification using wide bandwidth intracranial EEG (iEEG) in patients undergoing evaluation for epilepsy surgery.

Approach—Data from seven patients (age 34 ± 12 , 4 women) who underwent intracranial depth electrode implantation for iEEG monitoring were included. Spectral power features (0.1 – 600Hz)

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Contributions

Vaclav Kremen: methodology design, data pre-processing, mathematical calculation and machine learning, results and figures, writing the manuscript.

Juliano J. Duque: data pre-processing, spectral power calculations, figures and plots, editing manuscript.

Benjamin H. Brinkmann: data pre-processing, imaging & coregistration of electrodes, figures.

Brent M. Berry: Recording data, seizure onset localization, methodology design, sleep staging, editing manuscript.

Michal T. Kucewicz: data collection, editing manuscript.

Fatemeh Khadjevand: Data collection, setting up recording, sleep staging.

Jamie Van Gompel: electrode implant planning, implanted electrodes and assisted with recordings.

Matt Stead: recordings.

Erik K. St Louis: sleep staging.

Gregory Worrell: clinical care of patient, electrode implant planning, recording data, seizure onset zone localization, methodology design, writing the manuscript.

spanning several frequency bands from a single electrode were used to train and test a support vector machine classifier.

Main results—Classification accuracy of $97.8 \pm 0.3\%$ (normal tissue) and $89.4 \pm 0.8\%$ (epileptic tissue) across seven subjects using multiple spectral power features from a single electrode was achieved. Spectral power features from electrodes placed in normal temporal neocortex were found to be more useful (accuracy $90.8 \pm 0.8\%$) for sleep-wake state classification than electrodes located in normal hippocampus ($87.1 \pm 1.6\%$). Spectral power in high frequency band features (Ripple (80 – 250 Hz), Fast Ripple (250 – 600 Hz)) showed comparable performance for AW and SWS classification as the best performing Berger bands (Alpha, Beta, low Gamma) with accuracy 90% using a single electrode contact and single spectral feature.

Significance—Automated classification of wake and SWS should prove useful for future implantable epilepsy devices with limited computational power, memory, and number of electrodes. Applications include quantifying patient sleep patterns and behavioral state dependent detection, prediction, and electrical stimulation therapies.

Keywords

intracranial EEG; behavioral states; sleep staging; machine learning; classification

1. Introduction

Automated behavioral state classification should prove useful for implantable epilepsy devices, and would make possible behavioral-state-dependent seizure prediction (Cook et al. 2013; Brinkmann et al. 2015; Brinkmann et al. 2016; Ramgopal et al. 2014), and electrical stimulation therapies (Bower et al. 2015; Lundstrom, B.N et al. 2016; Salanova et al. 2015). The effect of behavioral state on human scalp EEG is the cornerstone of sleep scoring (Rechtschaffen and Kales 1968). The cerebral generators of sleep-specific EEG activity (Buzsaki 2006), including K-complexes (Cash 2009, Loomis 1937), spindles (Andrillon 2011), and slow waves (Nir 2011) (Cserscsa 2010) have been investigated using intracranial EEG (iEEG) recordings from patients undergoing evaluation for epilepsy surgery. Intracranial EEG recordings have been used in to characterize specific spectral (Le Van Quyen M et al. 2010)(Klimes P. et al. 2016)(Botella-Soler 2012, Nishida et al. 2005), spatial, structural and temporal characteristics (Nobili et al. 2012, Ferrara and De Gennaro 2012) of brain activity during wake and sleep behavioral states. However, there has been relatively little investigation into the feasibility of rigorous sleep staging using iEEG recordings (Kelsey et al. 2012) (Pahwa et al. 2015) (Zempel et al. 2012) and none of the previous studies have directly investigated different brain structures and the impact of tissue pathology, i.e. seizure onset zone (SOZ) or non-seizure onset zone (NON-SOZ).

Here we explore the feasibility of supervised automated wake (AW) and slow-wave sleep (SWS) classification using wide-bandwidth iEEG (0.1 – 600 Hz) (Worrell 2012) and Support Vector Machines (SVM) classifiers in patients undergoing evaluation for epilepsy surgery. We investigated the spectral characteristics and patterns of activity inside and outside of focal seizure-generating brain regions (i.e. SOZ and NON-SOZ) in two distinct human behavioral states and the feasibility of automatically differentiating between AW and

SWS behavioral states using multiple frequency bands. We demonstrate that using single iEEG channels can yield accurate automated classification of AW and SWS evaluated by the gold standard, polysomnography (Iber et al. 2007). Future implantable medical devices for epilepsy may benefit from accurate sleep/wake staging in order to quantify patient sleep patterns, enable administration of behavioral-state-specific therapies, and modulate seizure detection and forecasting algorithms.

2. Methods

Data were recorded from patients undergoing evaluation for epilepsy surgery at Mayo Clinic Rochester, MN. The Mayo Clinic Institutional Review Board approved the study, and all subjects provided informed consent. The subjects underwent intracranial electrode implantation as part of their clinical evaluation for epilepsy surgery when non-invasive studies could not adequately localize the origin of seizure generation, i.e. seizure onset zone (SOZ).

Subjects

Data from seven subjects with medial temporal lobe focal epilepsy were investigated retrospectively. All subjects were implanted with intracranial depth electrodes; each depth electrode consisted of either 4 or 8 recording contacts, and all subjects had simultaneous scalp EEG recordings for sleep scoring.

Electrodes and Localization

Depth electrode arrays (AD-Tech Medical Inc, Racine, WI) consisted of a 1.3 mm diameter polyurethane shaft with Platinum/Iridium (Pt/Ir) clinical macroelectrode contacts. Each contact was 2.3 mm long with 10 mm center-to-center spacing (surface area 9.4 mm² and impedance 200–500 Ohms). Anatomical localization of electrodes was achieved by co-registering post-implant CT data and co-registered to the patient's high resolution MRI using a normalized mutual information algorithm (SPM8, Wellcome Trust Centre for Neuroimaging), illustrated in Figure 1. Electrode coordinates were then automatically labeled by using the SPM Anatomy toolbox, with an estimated accuracy of 5 mm (Tzourio-Mazoyer et al. 2002).

Signal Recordings

All iEEG data were acquired using a common reference, a stainless steel scalp suture placed in the vertex region of the scalp, midline between the international 10–20 Cz and Fz electrode positions. The data was acquired with a Neuralynx Cheetah electrophysiology system (Neuralynx Inc.) using a 9 kHz antialiasing analog filter, digitized at 32 kHz sampling rate, filtered by low pass zero phase shift 1 kHz antialiasing filter and down sampled to 5kHz.

SOZ localization

The SOZ electrodes and times of seizure onset were determined by identifying the electrodes with the earliest iEEG seizure discharge. Seizure onset times and zones were

identified by visual review of iEEG recorded electrographic seizures, as described previously (Worrell et al. 2004; Warren et al. 2010; Klimes et al. 2016).

Sleep scoring with scalp EEG

Behavioral state was determined with scalp EEG signals and scored visually by a neurologist board-certified in sleep medicine (EKS). All EEG scalp recordings were bandpass filtered between 0.3 and 75Hz, and 60Hz notch filtered for scoring using third order linear phase Butterworth filters. Visual sleep scoring was in accordance with standard methods (Iber et al. 2007) with modification for replacing the electrooculogram (EOG) recording with FP1, FP2, and FPZ scalp electrodes. Standard length of epoch (30 seconds) with no overlap was used for scoring (Iber et al. 2007). Wakefulness was determined by the presence of eye blinks visualized in frontal scalp leads, accompanied by posteriorly dominant alpha rhythms (8 – 12 Hz) posteriorly, comprising >50% of the epoch. Slow-wave sleep (N3) was scored when high-voltage (>75 μ V), low frequency delta (0.5 – 2 Hz) activity on scalp EEG was present in at least 20% of the epoch (i.e., at least 6 s within a 30 s epoch) in the frontal derivations using conventional International 10–20 System electrode placements (FP1, FP2, FZ, F3, F4, CZ, C3, C4, O1, O2, and Oz). A similar approach has been used in previous studies (Bower et al. 2015, Klimes et al. 2016).

Data Pre-processing

Prior to analysis, continuous scalp and intracranial EEG from each patient were reviewed using a custom MATLAB viewer (Brinkmann et al. 2009). Channels and time segments containing significant artifacts, epileptiform discharges or seizures were not included in subsequent analysis.

Feature Extraction

All iEEG signals were filtered into nine frequency bands as follows: $b = \{0.1 - 4 \text{ Hz}, 4 - 8 \text{ Hz}, 8 - 13 \text{ Hz}, 13 - 30 \text{ Hz}, 0.1 - 25 \text{ Hz}, 25 - 55 \text{ Hz}, 65 - 100 \text{ Hz}, 100 - 250 \text{ Hz}, 250 - 600 \text{ Hz}\}$. iEEG signals were filtered using 6th order bandpass Butterworth filters in a zero-phase filtering approach. For frequency bands below 55 Hz, signals were decimated (by a factor of 500 for 0.1–4 Hz band and 25 for other bands) before applying the bandpass filter, to avoid filter instability. The spectral power in each frequency band was calculated for all electrodes across all subjects for each 30 second epoch, directly corresponding to the 30 second epochs sleep staged from scalp EEG. Power was quantified as an epoch average energy of filtered

time series defined by equation $P_{Abs}(s, e_s, b, k) = \frac{1}{N} \sum_{n=1}^N V(n)^2 [\mu V^2]$, where $s = \{1, \dots, 7\}$ is subject number, $e_s = \{1, \dots, \max_{1 \leq s} 7e_s\}$ is given electrode, $b = \{1, \dots, 9\}$ is frequency band, $k = \{1, \dots, 120\}$ is epoch of dataset (training/testing dataset joined with validation dataset, see 2.6 below), N is the number of data points in each 30 second epoch, and $V(n)$ is the unipolar voltage at given discrete time n in μV . Relative spectral power levels were calculated as follows:

$$P_{Rel}(s, e_s, b, k) = \frac{P_{Abs}(s, e_s, b, k)}{P_{Abs}(s, e_s, 5, k)} [AU]$$

to assess the ratio of each band power to power of low frequency bands (0.1–25Hz). All measurements formed a final set of features and classes $\mathcal{T} = (\mathbf{x}_i, y_i)$, where: $\mathbf{x}_i$ is a vector of features $\{P_{Abs}, P_{Rel}\}$ for given patient, electrode, and epoch; y_i is sleep score (class) corresponding to this epoch; and i is an index of epoch. To assess accuracy of classifier using defined features $\{P_{Abs}, P_{Rel}\}$ together with features randomly generated we created a set of normally distributed random features $\{P_{Rand}\}$ to extend the input of classifiers.

Awake and Deep Sleep Data Set

Based on sleep scoring and quality of iEEG signals in given segments, data $\mathcal{T}_T = \mathcal{T}(\mathbf{x}_i, y_i)$, $i = \{1, \dots, 40\}$ of consecutive 10 minutes of deep sleep (SWS) and consecutive 10 minutes of awake (AW) from one day/night were selected as a training and testing datasets. Conversely, dataset $\mathcal{T}_V = \mathcal{T}(\mathbf{x}_i, y_i)$, $i = \{41, \dots, 120\}$ of consecutive 20 minutes of N3 and consecutive 20 minutes of AW epochs was formed from other day/night periods of interictal iEEG to create an out-of-sample validation dataset. Both constructed training/testing ($\mathcal{T}_T$) and validation ($\mathcal{T}_V$) datasets of iEEG recording were created for all subjects and all electrodes in the study. All iEEG data were visually inspected to avoid inclusion of data with serious artifacts (high power of all harmonics of power line interference, flat line artifacts, movement, and low frequency artifacts).

Statistical Analysis and Machine Learning Approach

To determine statistical significance of the differences between features in AW and SWS sleep stages, the nonparametric Wilcoxon rank sum test was used. Data were graphically displayed in box-and-whisker plots and histograms. For feature selection, we maximized the area between the empirical receiver operating characteristic (ROC) curve and the random classifier slope using only the original $\mathcal{T}_T$ training dataset. Features from $\mathcal{T}_T$ for a specific electrode of each subject were used to train a set of classifiers in a ten-fold cross-validation (CV) procedure (Hastie et al. 2009). The Training dataset $\mathcal{T}_T$ was used in a 10-fold CV

estimate of prediction error $CV(\hat{f}, \alpha) = \frac{1}{3} \sum_{i=1}^3 L(y_i, \hat{f}^{-k(i)}(x_i, \alpha))$. The assignment of a trial to a specific partition $k: \{1, \dots, 7\} \mapsto \{1, \dots, 10\}$, where k serves as an indexing function that indicates the partition that observation i was allocated by uniform random permutations and made ratio $\frac{7}{10}$ training and $\frac{3}{10}$ for testing in every CV fold, $\hat{f}^{-k}(x, \alpha)$ is α th model fit with k th part of the data removed, and y_i is a class corresponding to i th vector of features. Subsequently, out of $\alpha: \{1, \dots, 10\}$ runs of CV, a classifier $\hat{f}(x, \hat{\alpha})$ that minimizes the estimated test error curve $CV(\hat{f}, \alpha)$ was selected as a result of every particular CV procedure. In cases with more than one classifier candidate for selection, one representative classifier was selected randomly, which resulted in selection of one classifier for each electrode. Prediction accuracy of selected classifiers was subsequently validated using an out-of-sample data segment $\mathcal{T}_V$ from each electrode and patient. All results reported in this paper relate to out-of-sample data validation. For this binary classification problem, a support vector machine (Cortes and Vapnik 1995) was used - a binary classification algorithm that finds an optimal hyperplane in feature space to separate given data into two classes y_i (either AW or N3). This algorithm has been used previously in iEEG pattern classification (Lee 2003, Quandt 2012, Liu 2010, Brinkmann 2015 PLoS One). A repeatability measures (mean and standard

deviation of an error) were calculated using ten runs of method under same conditions (e.g. number of features selected).

Method for AW and SWS classification

A schematic of the Automated Behavioral State Classifier (ABSC) method for behavioral state classification and its utilization is shown in Figure 2. Because it is a supervised method it requires training on gold standard data for each patient. Here 10 minutes of AW and 10 minutes of SWS were used to train the classifier using simultaneous scalp and intracranial EEG data. The trained classifier was then deployed on out-of-sample data using the optimal intracranial electrode that was automatically selected during training. Note that the user can restrict number of channels or features to be used, or specify set of channels or features to be used with automated feature selection turned on or off.

3. Results

In total, we analyzed 420 minutes (840 epochs) of EEG and iEEG from 7 subjects (34 ± 12 years old, 4 female, 65 electrodes in NON-SOZ and 33 electrodes in SOZ). The patients all had medial temporal lobe epilepsy, see supplementary data). Analysis of features aggregated across all electrodes and all subjects showed that the mean spectral power feature (both absolute and relative) in AW and SWS were different for delta, theta, alpha, low gamma, high gamma, ripple and fast ripple frequency bands ($p < 0.01$). Figure 3 shows histograms of relative spectral power features in AW and SW. When considering individual subjects, both absolute and relative spectral power are different in AW and SWS for 6/7 subjects in the Delta (0.1–4Hz) frequency band, with lower power in AW than SWS, whereas in Alpha, Beta, High Gamma (65–100Hz) and Fast Ripple (250–600Hz) bands, power is higher during AW compared to SWS for all subjects ($p < 0.05$) (Figure 4).

Classification of Awake (AW) and Slow Wave Sleep (SWS)

Training a classifier for AW and SWS using all NON-SOZ or SOZ electrodes from all patients produced a classification error of $19.9 \pm 10.5\%$ and $31.6 \pm 11.4\%$, respectively. For comparison using all NON-SOZ or SOZ electrodes from individual patients to train patient specific classifiers, and then averaging performances across all patients, yielded a classification error of $16.7 \pm 11.7\%$ and $17.0 \pm 15.4\%$, respectively (see supplementary data Table 1.).

We tested the performance of the Automated Behavioral State Classifier (ABSC) method with different numbers and subsets of features in SOZ and NON-SOZ electrodes. Figure 5. shows the performance of the ABSC method and repeatability (ten runs) for both SOZ and NON-SOZ using different numbers of features. As expected, better performance is achieved with NON-SOZ electrodes compared to SOZ electrodes.

The performance and repeatability of the ABSC method applied to NON-SOZ electrodes with different numbers of absolute or relative features is shown in Figure 6. Over all, a higher accuracy is achieved using relative spectral features compared to absolute spectral features ($p < 0.01$). The optimal performance was achieved using 4 and 5 relative spectral features.

Figure 7 shows performance of the ABSC method using only the four absolute or relative Berger bands features compared to any four absolute or relative features, i.e. the automated algorithm selects the optimal set of four features from Berger and high frequency (Low Gamma, High Gamma, Ripple, Fast Ripple). Optimal performance and lowest error is achieved using the automated feature selection with four features selected from all relative features (Figure 6 and 7). This result supports that classification of AW and SWS is optimized using a combination of relative Berger and high frequency band features.

For reference we also calculated performance of individual features using the same repeatability experiment as above (Table 3.). Results shows high single electrode and single feature discriminability (error $\sim 10\%$) for relative features from Alpha, Beta, Low Gamma, Ripple and Fast Ripple bands.

To explore the impact of brain anatomy (hippocampus vs. neocortex) we restricted the input of the classifier (Figure 2) to specific brain structures (Table 1), and found that the method performed more accurately on NON-SOZ neocortical electrodes (error $9.2 \pm 0.8\%$) compared to NON-SOZ hippocampus (error $12.9 \pm 1.6\%$)

4. Discussion

Determination of AW and SWS behavioral states using intracranial electrodes is motivated by potential applications for real-time behavioral state classification in implanted devices providing seizure forecasting (Cook et al. 2013; Brinkmann et al. 2015; Brinkmann et al. 2016) and state dependent therapeutic stimulation (Bower et al. 2015). We explored the feasibility of classification between two distinct behavioral states, AW and SWS, and demonstrated at the group level, patient level, and single electrode level that iEEG spectral bands can be used for automated classification using supervised learning in SVM with only ten minutes of AW and SWS data. In practice, this means that only 20 minutes of scalp EEG needs to be manually scored for adequate training data. We showed (Table 3) that a single power in band feature from only one electrode was enough to train a high accuracy SVM classifier ($>90\%$ accuracy, bold in Table 3.), in contrast to prior studies using a substantial set of electrodes and features (Pahwa et al. 2015 and Zempel et al. 2012).

Here we demonstrate that, in agreement with prior work (Kelsey et al. 2012, Pahwa et al. 2015, Zempel et al. 2012), AW/SWS differentiation is most accurate in NON-SOZ brain regions. Investigations of patients with focal epilepsy using wide bandwidth (0.1–600Hz) iEEG have demonstrated that interictal Gamma, Ripple, and Fast Ripple (Worrell 2004, Bragin 2000, Worrell 2008) activity is increased in the SOZ. Thus the classification of behavioral state in the SOZ compared to NON-SOZ was tested, and while NON-SOZ performance was superior, a SOZ classification accuracy of $\sim 90\%$ was achieved. This supports deployment of such methods in cases where all implanted electrodes are in the SOZ, without NON-SOZ electrodes, or SOZ determination is unknown.

Our data (Figure 6 and 7) suggests that high frequency features are useful for automated sleep staging, as automated feature selection on combined high frequency and Berger bands features improved results when using four and five classifier features. The optimal classifier

obtained using the ABSC method uses automated feature selection from combined Berger and high frequency band features (for N=4,5, accuracy 98%). Further, accuracy 90% using a single high frequency feature and optimal electrode was achieved with both high frequency (Low Gamma, Ripple and Fast Ripple) and Berger band (Alpha, Beta) relative features (Table 3).

We also analyzed hippocampus and temporal neocortex, which have characteristic differences in spectral power. We found persistent differences in behavior state classification between these two brain regions, which deserves future study. In the current study we found that NON-SOZ regions of temporal neocortex were more accurate for classification, but the difference in accuracy between neocortex and hippocampus electrodes was ~3%, which supports the use of hippocampus electrodes for automated sleep staging in cases where no neocortical electrodes are present.

Compared to Pahwa (Pahwa et al. 2015) and Zempel (Zempel et al. 2012) where substantial number of electrodes and a large feature space was used to train classifiers, here we tested and present an automated robust approach on a simple set of wide band (0.1–600Hz) PIB features. High accuracy classification of AW and SWS using a single electrode was achieved by training on a small amount (20 minutes) of supervised data (manual scoring from scalp).

Further study is needed to explore the feasibility of differentiating other sleep stages, including light non-rapid eye movement sleep (i.e. N1 and N2), REM sleep, and wakefulness using iEEG.

5. Conclusion

We investigated behavioral state classification (wake & slow wave sleep) using wide bandwidth (0.1 – 600 Hz) intracranial EEG spectral power features in a SVM supervised learning algorithm. The approach achieved high accuracy with electrodes in NON-SOZ (97.8±0.3%) or SOZ (89.4±0.8%) brain regions. The optimal results use a mixture of absolute and relative wide bandwidth spectral power features, but also achieved excellent performance (97.3±0.8%.) using only relative spectral power features from a single electrode. Future implantable devices for epilepsy may benefit from accurate sleep/wake staging in order to quantify patient sleep patterns, give behavioral state specific therapies, and adjust seizure forecasting classifiers.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1. MRI-CT co-registered electrodes

Post-implant CT images were co-registered to the patient's presurgical MRI. Illustrated is an occipital approach implant of mesial temporal lobe with an 8 contact depth electrode along the axis of the hippocampus in a patient with drug resistant epilepsy.

Figure 2. Automated Behavioral State Classifier (ABSC)

Schematic of the method for AW and SWS classification, training, and classifier deployment. Gold standard sleep scoring performed from scalp is used (10 minutes of AW and 10 minutes of slow wave sleep data required). Sleep scoring and multi-channel iEEG data are used in subsequent automated steps for feature extraction or selection (if turned on). Cross-validation is used to test classifiers. The single electrode yielding the best classifier is selected in last step of training. The trained classifier is applied to out-of-sample data, with features extracted from the selected electrode and then supplied to trained SVM that returns an AW or SWS classification. The user can select and restrict the number of channels, number of features, and whether automated feature selection is used.

Figure 3.

Histograms presenting distributions of relative spectral power feature (P_{Rel}) in 6 different spectral bands in AW and SWS stages. Aggregated data from all patients is displayed for different frequency bands for all analyzed electrodes (first row), only SOZ (second row) and only NON-SOZ electrodes (third row) separately (outliers are not shown).

Figure 4. Awake (AW) and Slow Wave Sleep (SWS) mean spectral power feature of each subject for different frequency bands in non-seizure generating brain (NON-SOZ)

Relative power feature of Delta (0.1–4Hz) is lower in AW than in SWS, and higher in all bands above the theta frequency range, including Alpha (8–13Hz), Beta(13–25Hz), Low Gamma (25–55Hz), High Gamma (65–100Hz), Ripple (100–250Hz) and Fast Ripple (250–600Hz) during AW compared to SWS. Wilcoxon signed-rank test indicates subjects (paired) AW and SWS means are significantly different ($p < 0.05$) in all bands, except for Theta (4–8Hz, $p = 0.58$).

Figure 5. Comparison of performance and repeatability (error bars from 10 trials) of the Automated Behavioral State Classifier (ABSC) for SOZ and NON-SOZ using different numbers of features

Better classification performance is achieved using NON-SOZ (red) compared to SOZ (blue) electrode. Performance of NON-SOZ is below 10% error using a single feature, while for SOZ the method needs to use at least 5 features to achieve error 10%. Error bars are calculated using data from all patients on the out-of-sample validation dataset.

Figure 6. Comparison of performance and repeatability of the Automated Behavioral State Classifier (ABSC) method in NON-SOZ using absolute (----) or relative (—) sets of features For more than two features ($N > 2$) lower error is achieved with relative spectral features compared to absolute spectral features, (* denotes $p < 0.01$ for each value of N). The optimal performance was achieved with 4 relative spectral features. Error bars are calculated from 10 trials on all out-of-sample data.

Figure 7. Behavioral state classification using four features

The classification error using the Automated Behavioral State Classifier (ABSC) method restricted to only the 4 absolute (blue) or 4 relative (pink) Berger band features. For comparison, behavioral state classification was performed with the ABSC method using any four absolute (black) or relative (red) features. The best performance was achieved using relative features. Note, when any 4 relative features is allowed (Berger and high frequency bands) the classification error (red) is lower then when the algorithm is restricted to only Berger band features (pink and blue).

Table 3

Comparison of performance using a single feature and the optimal NON-SOZ electrode. Average Error and Standard Deviation are calculated by running the method 10 times. Errors 10% are in bold.

Features in Bands	Absolute Features		Relative Features	
	Average Error	STD	Average Error	STD
Delta (0.1–4Hz)	13.3	0.27	16.07	0.57
Theta (4–8Hz)	7.32	0.32	13.17	0.78
Alpha (8–13Hz)	5.89	0.16	6.57	0.15
Beta (13–25Hz)	6.64	0.32	6.18	0.2
25–55Hz	11.79	0.38	5.54	0.63
65–100Hz	13	0.44	10.89	0.13
100–250Hz	17.93	0.86	10	0.95
250–600Hz	9.46	0.16	7.32	0.52