Meditation Training and Neurofeedback Using a Personal EEG Device

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Abstract

The neuroscientific literature provides evidence that meditation may have measurable effects on the electrophysiological activity of the brain. We utilize a single-sensor EEG device to compare meditation and baseline epochs from a cohort of 31 long-term meditators from Tibetan and Indian monastic backgrounds. We show that our support vector machine approach can distinguish between these two states with balanced success rates over chance, and in some cases over 90% on a second-to-second basis.

Introduction

Over the past several years, a host of simple consumer electroencephalography (EEG) devices have been released at relatively inexpensive price points. These devices allow single or multi-channel recording of EEG, generally employing user-friendly design, e.g. wireless headsets and impedance matching "active electrodes" which do not require gels or saline solution.

It is an open question whether such devices can be utilized for neurofeedback applications such as meditation training. A number of studies have noted that meditation appears to be marked by quantifiable changes in neural activity patterns (Lutz et al 2004, Ott et al 2010, Yu et al 2011). However, a coherent framework for these findings remains elusive. A recent review of more than 50 publications in the EEG meditation literature found a variety of state and trait changes associated with various types of meditation (Cahn and Polich 2006). The confusion in comparing different types of meditation is further compounded by speculation that even specific types of meditation, such as mindfulness meditation, may in fact represent umbrella terms for multiple cognitive and hence neural subsystems that interact in complex ways (Holzel et. al 2011).

While clearly still in its early stages, meditation EEG research has in some cases been driven by a singular focus on finding a particular EEG frequency which is strengthened or attenuated by meditation practice. Instead, we apply a machine learning approach and transform the problem into one of prediction: can we distinguish between the baseline and meditation state using the power in multiple frequency bands simultaneously? High-dimensional data like this has been tackled with some success in computational biology by classification approaches like support vector machines (Ben-Hur et al 2008), a technique highly suited for a system with such non-linear dynamics as the brain.

Methods

Baseline and meditation data was obtained from 31 long-term meditation practitioners using the single-sensor right prefrontal EEG system produced by Neurosky, Inc. Each subject was asked to complete a 5 minute resting period in which they were asked to close their eyes and let their mind wander (without meditating). This was followed by 15 minutes of meditation during which they were asked to perform whatever type of meditation was most familiar.

Preprocessing

For all subjects, the power spectrum in eight commonly-examined frequency bands was computed on a second-by-second basis, resulting in 31 datasets each composed of 8 vectors labeled as either "baseline" or "meditation". The number of 8 vectors in each dataset corresponded to the total number of seconds in both baseline and meditation epochs. These datasets were normalized by dividing each vector by its L2 Euclidean norm, after which classification using a support vector machine approach was performed.

Classification

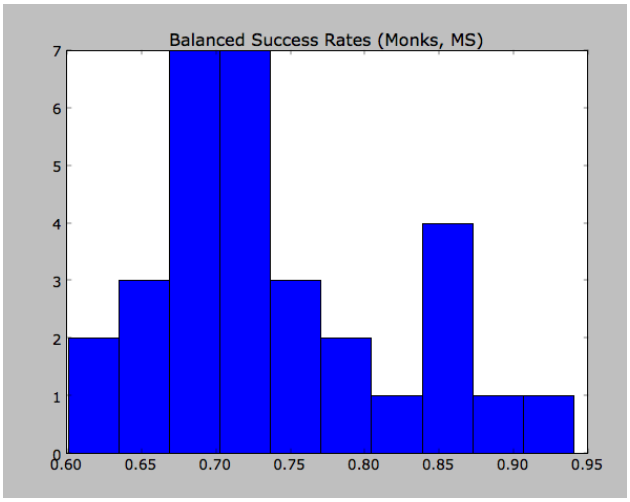
We utilize the PyML open source machine learning framework (Ben-Hur 2009) for classification. Model selection was performed using a grid search, whereby 20 pairs of gamma and C parameter values were evaluated according to maximum area under the receiver-operating curve.

Since the training classes for each dataset were unequal, a stratified cross-validation approach was used. This

approach is a better one when data classes are unbalanced, as it samples in proportion to class size. A five-fold cross validation was used in which four-fifths of the data was used for training the SVM, while the remaining fifth was left as test data. This process was repeated five times to provide average balanced classification accuracies for each dataset.

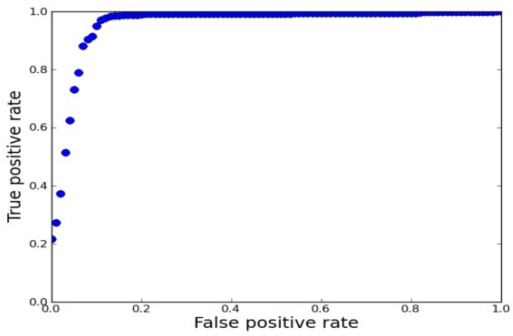
Results

We find our classification approach is able to distinguish between the baseline and meditation state on a second-by-second basis with a mean balanced success rate of 75.7%. The histogram of each subject's individual balanced success rate is included below.



Histogram of the balanced success rates of the SVM for each long-term meditation practitioner after model selection (MS) and 5-fold cross-validation.

In the best cases, we are able to classify with over 90% accuracies and with areas under the ROC of 0.940.



A sample ROC curve (0.940) from the subject with the highest balanced success rate (from the sample population.

Conclusion

We show that single-sensor consumer EEG devices may have potential in detecting meditation, and hence facilitating its training via various neurofeedback protocols. Questions about the generalizability of our results to novice and intermediate practitioners remain to be answered in further study.

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