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Is Meditation Measurable?

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Abstract. This paper discusses how to utilize entropy to brain states classification based on EEG recordings. We use 3 different classification models, one is tree based, one is distance based, and the other is probability based. We discuss the suitability of 2 types of entropy: approximate entropy, and sample entropy in different circumstances. With proper choice of parameters, misclassification rate is less than 5%. Sample entropy is a good tool to extract information from EEG data.

Keywords: meditation; machine learning; electroencephalogram (EEG); entropy; classification

1. Introduction

As described in the famous book of Patriarch Zhi Kai (AC 523-597) [1], which gives the detailed methods of Dharma practice, there are four Dhyana stages, each having specific bodily manifestations. This gives justification for developing a physiological model of “meditation” state and using data analytics methods to test the proficiency level of meditation.

Implied by the fact that a goal of meditation is total self-control of thoughts, the effects of meditation should be reflected by psychological indexes and in turn linked with physiological indicators. For example, Functional Assessment of Cancer Therapy --- General (FACT-G) [2] and Profile of Mood State [3]. Mruk & Hartzell proposed six Zen principles of psychotherapeutic value by analyzing the therapeutic value of meditation [4].

On the other hand, using electroencephalographic (EEG) data, cognitive psychologists can visualize and observe correlations between different active brain states. We present the design and implementation of an application that takes EEG data and exposes it to various analytical techniques so the resultant brain states can be studied and predicted. The presentation will consist of an extrication of the design of an EEG headset, which can collect EEG, pulse, and temperature data, and a case study in which EEG signals demonstrate differences between different brain states.

The presentation of this paper will be as follows. In the second section, we will present the design of an EEG headset and review how EEG can be used to measure brain states. In the third section, we will present the experimental results we have obtained. We will conclude the presentation therein.

2. Brain State Detection Using EEG Data

Galvani discovered that living organism demonstrates electrical activity [5]. Hans Berger successfully recorded electrical activity from the human brain by measuring voltage oscillations. Scientists also discovered five major brain waves, each linked to certain brain activities. For instance, Beta waves are

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associated with consciousness; alpha waves are indicators of disengagement [6]; theta waves are often shown in motionless but alert state [7]; and Delta waves are related to sleeping.

Here we briefly describe how a simple EEG headset can be built using open source materials. The prototype multi-functional headset we built consists of an EEG sensor, a pulse sensor, a temperature sensor, a microprocessor, and a microprocessor blue tooth shield.

(1) EEG sensor, commercial product from NeuroSky. The NeuroSky technology was chosen for its dry sensors capabilities. This means that the sensor requires no special liquid chemicals while making contact with the skin to read brainwaves.
(2) Pulse Sensor, Open Source pulse sensor from pulsesensor.com. The pulse sensor is a current to voltage converter Op Amp circuit that uses a photodiode as current source. It has a Low Pass Filter for output.
(3) Temperature sensor, commercial integrated circuit sensor, TMP36 - Analog Temperature sensor from Adafruit. The TMP36 temperature sensor is a solid state device. Meaning it does not use mercury. Instead, it uses the fact that as temperature increases, the voltage across a diode increases at a known rate. By precisely amplifying the voltage change, it is easy to generate an analog signal that is directly proportional to temperature.
(4) Microprocessor: Arduino Mega 2560, Open Source.
(5) Microprocessor Blue Tooth Shield: Bluetooth Low Energy (BLE) Shield from redbear.com. Added to the Arduino for low energy blue tooth communications with the iPhone.

The assembled headset is shown in Figure 1, where the 3 sensors are mounted on the tips of 3 legs in the forehead, the microprocessor and the microprocessor blue tooth shield are mounted on the back, and the ear lobe is used as the base of the EEG sensor.

Fig. 1: Prototype multi-functional headset

To show that the headset sensors are working a custom mobile application was developed to view the results. Sample screenshots of the application with the actual results are displayed in Figure 2. The left snapshot shows the signal strengths of the EEG sensor (the lower number) and the Arduino sensors (the upper number). Readings of the 3 sensors are shown on the right snapshot. Since we use the NeuroSky EEG sensor, the EEG signals are filtered into signals of different frequency intervals.

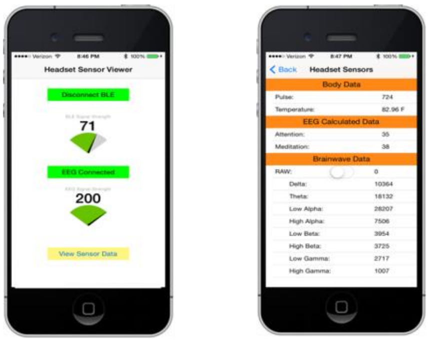

Fig. 2: iOS Sensor headset application

In healthcare and biomedical research, studies have been done to discover links between emotional states and brain activities using machine learning algorithms [8]. By analyzing EEG data collected during various emotional states from 40 Parkinson disease patients and healthy subjects using bispectrum feature, Yuvaraj et al concluded that the higher frequency bands such as alpha, beta and gamma played important role in determining emotional states compared to lower frequency bands, delta and theta. In a different study, Direito et al designed a model to identify the different states of the epileptic brain using topographic mapping relative to delta, theta, alpha, beta and gamma frequency [9]. The method achieved 89% accuracy in predicting abnormal vs normal brain states. These studies have revealed the variability in analysis due to two factors, viz., the feature extraction methods and the number of variables used in modeling. It is found that the model is directly proportional with the increase in the constant variables associated with the modeling equation.

We focus on the statistical classification methods to analyze EEG collected from different brain states to build a model, and then use the model to test EEG data to find out the subject's brain state. We consider using feature extractions from raw EEG data to improve the correct classification rates. Given that different areas of human's brain exhibit different features while the brain stays in the same state [10], and sometimes EEG record also changes spontaneously [11], multiple statistical classification methods are used in analyzing EEG data. Supervised machine learning models include tree bagging, boost [12], random forest [13], and support vector machine [14]. We also used unsupervised machine learning algorithms, such as hierarchy clustering. Moreover, entropy was used as features of EEG data to improve the classification rates. For example, sample entropy measures the uncertainty inside a sequence of data [15]. We explored the effects of different types of entropy.

3. Identifying Meditation State

The regularity observed in the brain waves of meditation state suggests that entropy might be a right feature to use in the classification of brain states including meditation state. Entropy was introduced to calculate complexity or regularity of the real world in 1991 [16]. Shannon entropy is the basis of various types of entropy calculations. Approximate entropy (ApEn) was introduced as an estimation for the imperfect biological data, while sample entropy (SampEn) is intended to measure the order in a time series [17].

We collected EEG data from subjects in three brain states, viz., idle, meditating, and talking, using Emotiv EPOC headsets. Based on our previous work, when we use tree bagging, we set number of trees equal to 2500, and we use linear kernel in support vector machine [18].

We firstly used approximate entropy as a feature in the machine learning procedure. We have misclassification rate of the above three methods in Table 2. Parameters are chosen by finding the largest mean of Hurst exponents of data. For GMM, we used EEE model type, which gave the least misclassification rate. This is also because approximate entropy from different channels had similar variances.

Table 2. Misclassification rates using approximate entropy

Parameter	Misclassification Rate		
	Tree Bagging	GMM	SVM
time = 1s, lag = 1	0.322	0.312	0.290
time = 1s, lag = 4	0.247	0.301	0.301
time = 10s, lag = 4	0.042	0.208	0.042
time = 20s, lag = 4	0.292	0.375	0.333
time = 30s, lag = 1	0.143	0.190	0.190

Table 3. Misclassification rates using sample entropy

Parameter	Misclassification Rate		
	Tree Bagging	GMM	SVM
time = 1s, lag = 1	0.065	0.065	0.075
time = 1s, lag = 4	0.140	0.161	0.108
time = 10s, lag = 4	0.042	0.042	0.042
time = 30s, lag = 4	0	0	0
time = 60s, lag = 4	0	0	0
time = 60s, lag = 6	0	0	0
time = 60s, lag = 12	0	0	0

We can see that when time length is 10s and embedding lag is 4, we have the smallest misclassification rate, which is around 4% given by either tree bagging or support vector machine. Compared to some of our previous misclassification results without using entropy (30% in [18]), this is significant improvement. Table 2 also shows that when using approximate entropy, the misclassification rate does not necessarily decrease when the time length increases. It is also observed that tree bagging has a higher likelihood to give the smallest misclassification rate.

We further test similar parameters and classification models using sample entropy to process EEG data. Unlike approximate entropy that is an estimation of the true entropy, sample entropy tends to measure the level of chaotic complexity of a time series data. We show our misclassification result in Table 3. It is clear that for sample entropy, with the increasing time length, misclassification rate decreases. This makes sense considering the nature of sample entropy.

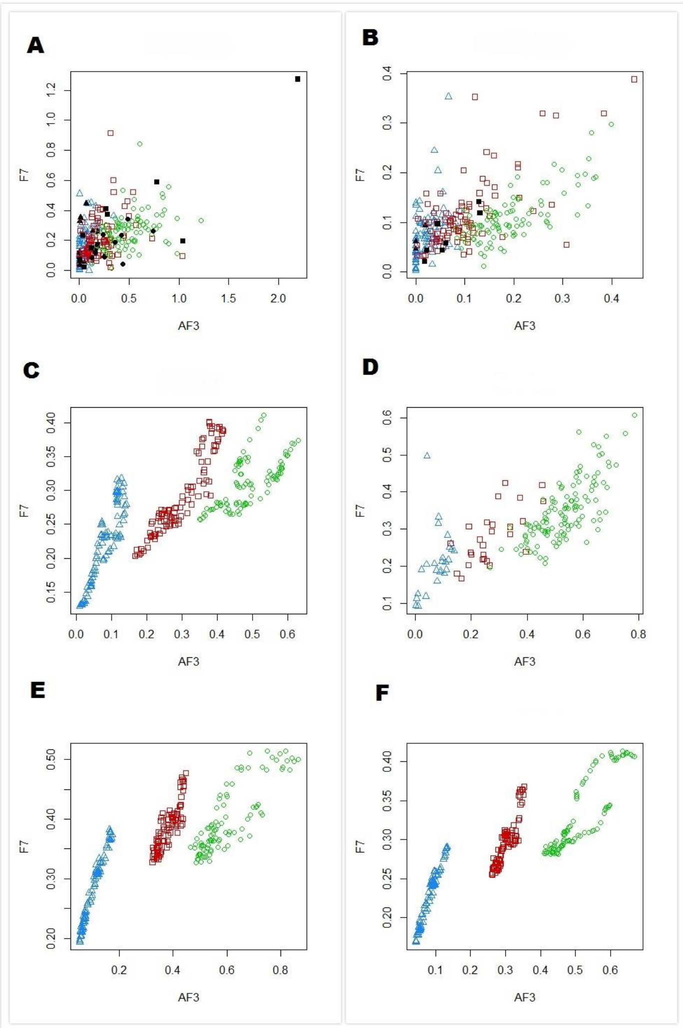

Fig. 3: Sample entropy with different parameters. A. Time = 1s, Lag = 4, B. Time = 1s, Lag = 1, C. Time = 30s, Lag = 4, D. Time = 10s, Lag = 4, E. Time = 60s, Lag = 4, F. Time = 60s, Lag = 6

We exhibit the plots of sample entropy of EEG recordings using different time length and embedding lag in Figure 3. In each graph, the triangles stand for sample entropy for talking, circles are sample entropy for mediation, and rectangles are sample entropy for being idle. Black filled shapes mark the misclassified data. We can see that with the increasing time length, sample entropy from different brain states tend to be more separated. We also notice that embedding lag becomes less influential when time length increases (A&B vs. E&F). We observe that tree bagging, in most cases, gives the smallest misclassification rates.

Comparing our results on approximate entropy and sample entropy, we conclude that when using original EEG data, sample entropy provides a more solid base to classify different brain states.

4. Concluding Remarks

In this paper, we present an experiment of using EEG data to classify meditation from other states. Our result shows that entropy, especially sample entropy, is a very useful tool in classifying different brain states. However, we notice that using R to calculate sample entropy is time consuming, especially when the time length grows larger. In the future, we will continue on improving computational performance.

Also, in classification using Gaussian mixture model, traditional BIC fails to be a useful benchmark to select the model type. It is traditional to choose the model that gives the highest BIC score. Here, as we can see, the best model type (EEE) does not give the highest BIC score. In the future, new selection criteria need to be established.

After all, our experimental results suggest that measuring meditation state using EEG data is feasible.

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