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Statistical Machine Learning in Brain State Classification using EEG Data

Yuezhe Li [A], Yuchou Chang [B], Hong Lin [B]

[A] Department of Mathematics, Illinois State University, Normal, IL, 61761, USA, yli3@ilstu.edu

[B] Department of Computer Science and Engineering Technology, University of Houston-Downtown, Houston, TX, 77002, U.S.A, {changy, linh}@uhd.edu

Abstract

In this article, we discuss how to use a variety of machine learning methods, e.g. tree bagging, random forest, boost, support vector machine, and Gaussian mixture model, for building classifiers for electroencephalogram (EEG) data, which is collected from different brain states on different subjects. Also, we discuss how training data size influences misclassification rate. Moreover, the number of subjects that contributes to the training data affects misclassification rate. Furthermore, we discuss how sample entropy contributes to building a classifier. Our results show that classification based on sample entropy give the smallest misclassification rate. Moreover, two data sets were collected from one channel and seven channels respectively. The classification results of each data set show that the more channels we use, the less misclassification we have. Our results show that it is promising to build a self-adaptive classification system by using EEG data to distinguish idle from active state.

Type of Paper and Keywords

Regular research paper: *Electroencephalography, EEG, brain state, classification, machine learning, sample entropy*

1 Introduction

Renowned scientist and philosopher Galvani was the first person to discover electrical activity in living organisms. Later Hans Berger successfully recorded electrical activity from the human brain using electroencephalography (EEG), which measures voltage oscillations [27]. An EEG records the electrical activity of a brain via electrodes affixed to an individuals scalp. Today, EEG is one of the popular non-invasive techniques to record brain activity in clinical and research settings. The development of cheap EEG devices, for example, EPOC from Emotiv and NeuroSky, helps increase the interests in studying EEG data in different brain states [19].

A human brain is composed of many interrelated but also anatomically separable areas. Different areas exhibit different features while the brain stays in the same state [9]. Sometimes EEG records also change spontaneously [5]. Thus, a statistical classification method is a useful tool in analyzing EEG data. Many modern machine learning algorithms and models have been successfully utilized in studying features hidden in EEG data collected from brains in different states. Supervised machine learning models include tree bagging, boost [24], random forest [6], and support vector machine [7]. Unsupervised machine learning algorithms, such as hierarchy clustering, are also utilized. Sample entropy, a method that aims to measure the uncertainty inside a sequence of data, also helps analyze brain activities through EEG records [20]. Different machine learning methods have different bases. Some are based on a decision tree; others are simply based on distance. Therefore, different classifiers exhibit different features. Our previous work shows that delta waves and theta waves change significantly between reading and meditation states.

Our experiments have shown that using only delta waves and theta waves that k-nearest-neighbor classifiers have misclassification rates between 15% and 35%, and support vector machine classifiers have misclassification rates between 15% and 85%. These results indicate that using these two types of brain waves can have very good classification results, but sometimes they may not be informative enough [13, 23, 4, 22]. Our experiments shows that besides theta and delta brain waves, that blink strength, another factor that can be measured by a Neurosky headset, also has a significant influence on brain state classification [18]. Based on all these result, we have designed an EEG data analysis system to classify brain states. However, it shows collinear it with different brain waves. As a consequence, when we build our brain state classifiers, we use brain waves and blink strength as mutually exclusive features.

In this article, we discuss how to classify EEG data collected from different brain states. We collected data from different subjects with their brains in different states. We used these data to build classification models and then tested these models using this data. We discuss how the training data size and the number of subjects influence the precision of our classifiers. We use data that was collected from 2 different headsets, EPOC made by Neurosky and EPOC made by Emotiv. The difference between the 2 headsets is the number of channels. In Section 2, we discuss performance of different classification algorithms in different situations using data collected by a Neurosky headset. In Section 3, we discuss the potential of using unsupervised machine learning to extract features from the amplitude of different brain waves. In Section 4, we demonstrate sample entropy is a good method to classify different brain states. It works even better with multiple channels.

2 Classification of Multiple Brain States from Multiple Subjects

In our work, we use data collected from both Neurosky headsets and Emotiv headsets. The data collected using Neurosky headsets is from 19 different subjects (volunteers). Neurosky headsets have a build-in system that can reduce the noise of the hardware and utilize embedded solutions for the signaling process and output [3, 12]. In our experiments, volunteers walk in, put on a Neurosky headset, and do what they are told to do (for example, play a video game). Data is recorded in a txt file. We drop the first minute of data, as we believe brains need time to adjust. Then, for each subject, the recording time is between 5 and 10 minutes. Thus, for each subject, every data entry is between 153600 and 307200 (sample rate 512 times per second). Some subjects, for example, subject C, as we will mention in Section 2.3, has the EEG data collected multiple times. The EEG data of each subject (volunteer) was acquired at different times and in 5 different states. Data collected using Emotiv headsets was from 5 subjects (volunteers) in 3 different states. Our classification models are built based on tree bagging, random forest, k-nearest neighbors, boost, and support vector machine.

2.1 Pooled Subjects with Multiple Brain States

We use pooled subjects with different brain states. By pooled subjects, we mean that data collected from the same subjects can be in a training data set, testing data set, and validation data set. We put all the data together regardless of when and who it was collected from, then we train our models and do classifications.

Data from 19 different subjects were collected using Neurosky headsets. Some data was collected in 2 different brain states, while other data was collected in 3 different brain states, for comparison. Our models used 11 variables: attention, blink strength, meditation, alpha low (8-9Hz), alpha high (10-12Hz), beta low (13-17Hz), beta high (18-30Hz), gamma low (31-40Hz), gamma mid (41-50Hz), delta (1-3Hz), and theta (4-7Hz).

We firstly used the validation data set to tune the parameters in the different models, then we used the training data set to train our models, and finally we plugged in the testing data set to see how the classification results differed from the true classes (Figure 1). Our models and parameters are:

- tree bagging
  - number of trees
- random forest
  - number of trees
  - number of variables
- k-nearest neighbor
  - number of neighbors
- boost
  - number of trees
  - shrinkage in every step
  - interaction depth
- support vector machine
  - kernels functions (linear, polynomial, sigmoid, and radial kernels), and parameters in kernel functions
  - restrictions on boundary (cost, ϵ)

Table 1: Classification for Pooled Subjects with 3 Different Brain States

Parameter: tree number=5000; shrinkage=0.0019; interaction depth=5;				
Misclassification Rate $= 0.001423$				
Boost		Predicted States		
		video	meditation	reading
True	video	530698	633	253
	meditation	542	493966	99
	reading	368	228	465026

Parameter: tree number=5000;				
Misclassification Rate = 6.837×10^{-5}				
Bagging		Predicted States		
		video	meditation	reading
True	video	494604	3	0
	meditation	0	465562	60
	reading	11	28	531545

Parameter: tree number=5000; number of vars=3				
Misclassification Rate = 6.64×10^{-5}				
Random Forest		Predicted States		
		video	meditation	reading
True	video	531545	11	28
	meditation	0	494607	0
	reading	60	0	465562

Parameter: k=4				
Misclassification Rate = 8.647×10^{-5}				
KNN		Predicted States		
		video	meditation	reading
True	video	531516	0	68
	meditation	61	494546	0
	reading	0	0	465622

Parameter: radial core, $\gamma = 1, \text{cost} = 20, \epsilon = 0.1$;				
Misclassification Rate = 0.042				
SVM		Predicted States		
		video	meditation	reading
True	video	133613	3882	1249
	meditation	1258	136200	1372
	reading	1506	2517	21208

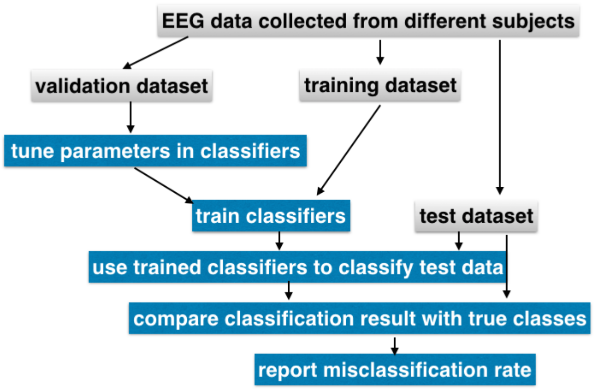

Figure 1: Prosedure of building a classifier

Detailed results regarding confusion matrices, parameters and misclassification rates are in Table 1 and Table 2. We also found that kernel functions have little impact on the misclassification rates of support vector machines ($< 2\%$, regardless of changing the kernel functions or the parameters in kernel functions), but choosing good restriction conditions for the boundary can largely improve the classification result. Thus, we used the radial kernel here. It is easy to see that they all have very low misclassification rates (most of them $< 4.2\%$; only boost for two brain states has a misclassification rate of 17%), regardless of whether there are 2 (in Table 2) brain states. Therefore, we conclude that pooled subjects models have very good classification results.

2.2 Different Subjects in Training and Testing

From the success that we mention in our previous section, it is natural to be curious as to what will happen if the training and testing data are from different subjects. Still using the previous models with the established parameters, the results worsened. The data we used to train our models was collected from 6 subjects. Then we used data from 6 other subjects to test our models. Every classification algorithm was run twice. Each time, we randomly chose 6 training subjects and used the rest as testing subjects. Also, we noticed that there were some continuous entries of data that were the same. Since we were not using any classification method related to time series, we removed these repeated entries, but kept one to accelerate the calculation speed.

Confusion matrices are in Table 3. The results are not ideal, as the misclassification rates increases to around 35%; the highest misclassification rate is 52.9%, which is far bigger than the misclassification rate reported in 2.1.

In order to decrease the misclassification rate, we used the majority vote here. That is, we used classification

Table 2: Classification for Pooled Subjects with 2 Brain States

Misclassification Rate = 0.015			
Tree Bagging		Predicted States	
		gaming	idle
True	gaming	42782	744
	idle	545	42672

Misclassification Rate = 0.172			
Boost		Predicted States	
		gaming	idle
True	gaming	37482	6047
	idle	8931	34286

Misclassification Rate = 0.024			
Support Vector Machine		Predicted States	
		gaming	idle
True	gaming	41404	2125
	idle	0	43217

results from tree bagging, boost, and support vector machine to do a majority vote. For example, for a certain entry of testing data, both tree bagging and boost classified it as meditation, while the support vector machine assigned it as reading, then majority vote assigned it to be in the meditation class. The confusion matrix is in Table 4. The misclassification rate decreases to 36.7%. It is better, but not significantly.

As shown in the Table 4, it is clear that most of the mistakes are made when classifying a subject that is in a meditation state, as there is only 35% correct classification of the test data from meditation. This is reasonable since all the subjects are not professionals in meditating. Thus, we will disregard meditation data in any future analysis. Moreover, the size of the training data set influences the misclassification rates. We provide a graph showing how misclassification rates change with increasing training data set sizes in Figure 2. Here, the data size increases five times, while the misclassification rate decreases 3%.

2.3 Training and Testing from the Same Subject

In this section, we investigate how the size of the training data set influences the misclassification rate. We focus on what if the training and testing data are from the same subject. From section 2.1, we assume that it should be good. Then we use data collected in 2015 from subject C to see how it works. We use data collected using Neurosky headsets from different times from subject C, and we use tree bagging, boost, support vector machine, and majority votes based on the previous three models to

Table 3: Different Classifications for Different Subjects

Misclassification Rate $= 0.529$ Correct Rate for True Brain State is Watch Video $= 0.534$ Correct Rate for True Brain State is Meditation $= 0.357$ Correct Rate for True Brain State is Reading $= 0.901$				
Bagging		Predicted States		
		watch video	meditation	reading
True	video	613	213	322
	meditation	587	382	100
	reading	230	154	426

Misclassification Rate $= 0.350$ Correct Rate for True Brain State is Watch Video $= 0.708$ Correct Rate for True Brain State is Meditation $= 0.357$ Correct Rate for True Brain State is Reading $= 0.949$				
Boost		Predicted States		
		watch video	meditation	reading
True	watch video	813	335	0
	meditation	34	382	635
	reading	0	42	778

Misclassification Rate $= 0.372$ Correct Rate for True Brain State is Watch Video $= 0.687$ Correct Rate for True Brain State is Meditation $= 0.355$ Correct Rate for True Brain State is Reading $= 0.901$				
SVM		Predicted States		
		watch video	meditation	reading
True	watch video	789	338	68
	meditation	56	379	634
	reading	2	79	739

Table 4: Majority Vote Classification for Different Subjects

Misclassification Rate $= 0.367$ Correct Rate for True State is Watch Video $= 0.687$ Correct Rate for True State is Meditation $= 0.333$ Correct Rate for True State is Reading $= 0.946$				
Confusion Matrix		Predicted States		
		video	meditation	reading
True	video	789	308	51
	meditation	56	356	657
	reading	2	42	776

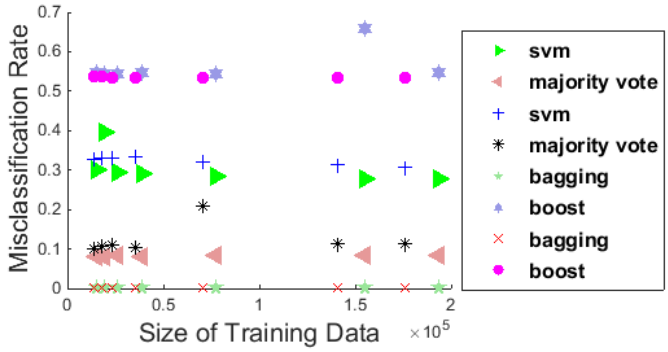

Figure 2: Misclassification rate with different training data size

(Explanation: This graph describes different classification methods' behavior towards increasing in training data size. Pentagon stands for misclassification rate using boost classifier, which gives the highest misclassification rate here. Rectangles are for support vector machine classifiers. Support vector machine classification is performed twice with different training and testing data that are collected from different subjects. Circles are misclassification rate given by majority votes based on tree bagging, boost, and support vector machine. Tree bagging, which marked by triangles, are the best classifier here. The misclassification rate is close to 0.)

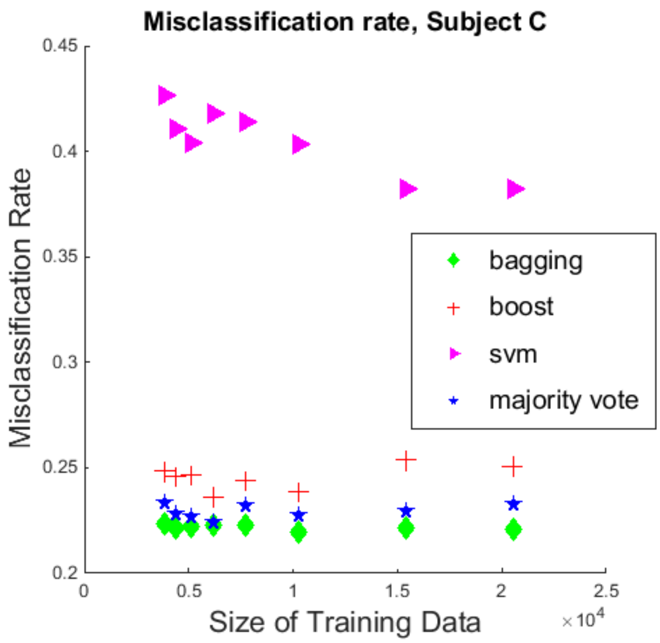

Figure 3: Misclassification rate with different training data size, subject C

(Explanation: In this graph, we compare misclassification rate with different size training data sets. Here, both training and testing data set are collected from the same subject, which is subject C. Subject C has been collected EEG data of 2 different brain states for multiple times. Here we change training data set by combining a different number of data sets collected from subject C. The testing data set is collected from a different time from training data set. Majority vote is based on tree bagging, boost, and support vector machine.)

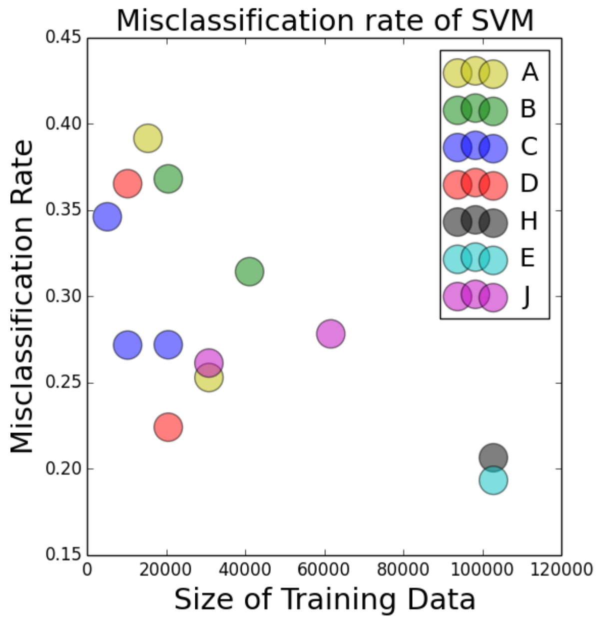

Figure 4: Misclassification rate with different training data size for support vector machine, subject A, B, C, D, E, H, J

(Explanation: In this graph, we present how training data size influences misclassification rate. Difference in training data set is result in difference in time length when collecting data, and in different combination of raw data set.)

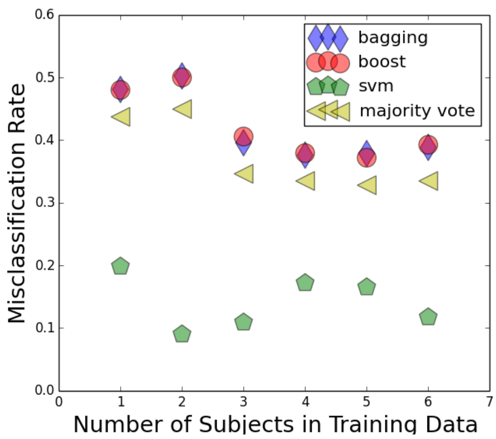

Figure 5: Misclassification rate with different training data size for support vector machine, subject A, B, C, D, E, H, J

(Explanation: Here we use subject C as our test data set. Training sets combination are as follows:

Subjects:	2	3	4	5	6
	E & H	A, E & H	A, B, E & H	A, B, D, E & H	A, B, D, J, E & H

)

see what happens when the training data size increases. Figure 3 illustrates that support vector machine classifications always give the highest misclassification rate (about 20% more). This implies the difference between brain states might not be directly associated with Euclidean distances between observation entries.

It can be seen that with the increasing size of training data, the support vector machine has the most significant decrease in misclassification rates. It is an interesting observation. We further investigate whether it is true among different subjects. We use data collected from subjects A, B, D, E, H, and J to see whether there is a similar pattern. Figure 4 shows a pattern that with the increasing training data set size, the misclassification rate for the support vector machine decreases by 41% at most. This result is significantly better than our previous result using only theta waves and delta waves.

2.4 Number of Subjects includes in Training Data

From the sections 2.1, 2.3, we assume that with increasing the number of subjects in the training data set, that the misclassification rate decreases. This is reasonable because the difference between sections 2.1 and 2.3, is how many subjects contribute to the training data set. Figure 5 gives more information about our experiment results. It is an interesting observation that with different training and testing data sets, the performance of different models changes.

For example, the support vector machine gives the best classification for this data set. The most significant decrease is given by a majority vote. Its misclassification rate decreases by 23% at most. However, it is also observed that the misclassification rate does not necessarily decrease when the number of subjects used in the training data set increases. This might imply that there are still lots of individual differences between different subjects.

3 Unsupervised Machine Learning

In this section, we consider unsupervised learning using EEG data. The reason we consider this situation is based on if the test data come from a class other than the classes presented in the training data. For example, in the training data, we could only have gaming and idle for two different brain states. We want to know whether it is possible to develop a classifier that is capable of reporting a state other than known states.

Consider the audacity of every different band of brain wave as dimensional coordinates, and then it is natural to consider whether it is possible to classify a data entry based on distance in a high-dimension Euclidean space. Following this idea, we use k-means clustering [28, 25]. K-means clustering is a vector quantization method grouping similar data entries [26, 21].Compared to supervised learning, it is only based on the feature that the data entry presented, but it is not related to the group it is supposed to be in. Here, we use leave-one-out cross-validation to see the performance of k-means clustering [1]. Detailed results are in Table 5.

Since we have no idea what might be the best number of clusters, we try from 2 to 6 to find the best parameters [25]. However, to our disappointment, it seems that little pattern exists. The two brain states are almost evenly distributed in different clusters, which is not quite different from random guessing. Thus, we conclude that k-means is not a good method to identify differences between these 2 known different brain states (gaming & idle). Compared to other studies showing k-means clustering is good at this might indicate that differences between normal brain states are more subtle compared to differences between neural spike or other pathological situations, or that other information, such as EOG (electrooculogram) or other filters, is needed in this situation [17, 14, 10]. Thus, here we conclude that unsupervised learning, which leaves out some information compared to supervised learning, is less effective. This result is consistent with the result we will present in our next section, where unsupervised learning performs well with extra feature extraction, more channels of EEG signal, and further assumptions.

4 Sample Entropy: Machine Learning Based on Feature

In this section, we will discuss using data collected from Neurosky headsets and Emotiv headsets. The most significant difference between these headsets is the number of channels, namely, the number of locations on the head where data is collected. While Neurosky headsets collect only one channel, Emotiv headsets collect 16 channels. Here we use the well connected seven channels from Emotiv headsets. We calculate the sample entropy of an individual with given brain states in 1 minute, and then we use sample entropy to do the classification. Classification models include tree bagging, boost, support vector machine, and the Gaussian mixture model.

Before calculating sample entropy, we normalize the data in each variable. Normalization is defined as follows:

$$\text{Normalized}(e_i) = \frac{e_i - E_{\text{min}}}{E_{\text{max}} - E_{\text{min}}} \quad (1)$$

where E_{min} the minimum value for variable E and E_{max} the maximum value for variable E.

Furthermore, we perform hierarchy clustering on sample entropy results to have a more thorough view of them.

Table 5: Data Entries Located in Different Clusters Created by K-means Clustering

Clusters Number		True Brain State	
		gaming	idle
2	1	557594	536260
	2	1910658	1931822
3	1	459710	424656
	2	1650628	1596870
	3	357914	446556
4	1	1442952	1384117
	2	378640	360144
	3	357914	446556
	4	288746	277265
5	1	294690	276753
	2	350480	310992
	3	1325449	1241404
	4	238535	287085
	5	259098	351848
6	1	1325449	1242404
	2	200638	284776
	3	288234	276753
	4	97884	111604
	5	378640	360144
	6	177407	193401

The Emotiv data were collected from 5 different subjects. There are three different brain states in the collected data: talking, idle, and meditating, which are labeled as 1, -1, and 0, respectively. For Emotiv headsets, the sampling rate is 128 times per second. Thus, every sample of entropy is based on 7680 (= 128*60 sample entries collected every minute) consecutive data entries. To keep up the quality of our data, we chose only the seven channels that are well connected to be in our training and testing data sets.

The Neurosky data were collected from 5 different subjects. There are four different brain states in the training and testing data: idle, gaming, from idle to gaming, and from gaming to idle, which are labeled as 0, 1, 2, and 3, respectively. For Emotiv headsets, the sampling rate is 512 times per second. Thus, every sample of entropy is based on 30720 (=512*60, sample entries collected in every minute) consecutive data entries.

4.1 Classification Based on Entropy

We split the data into two parts: training and testing. We used the training data to train our models and then plugged in the testing data to see what the prediction results would be. Confusion matrices of data collected through Neurosky headsets are in Table 6 and Figure 6 and Figure 7 (misclassification rate between 52% and 40%; lowest misclassification rate given by majority vote), Emotiv headset are in Table 7 and Figure 8 and Figure 9 (all misclassification rate = 0).

From the two figures, overlapping between different classes of data collected from Neurosky headsets is far more significant than data collected from Emotiv headsets. Apparently, misclassification rates for Neurosky data are higher than for Emotiv data. It is clear that the latter one gives a much better result than the former one, even though the former one is not bad.

4.2 Hierarchy Clustering Based on Entropy

We further perform hierarchy clustering on sample entropy to have a more thorough picture of their features. Hierarchy clustering results presented in dendrograms are in Figure 10. From here, it is clear that sample entropy calculated from data collected using Emotiv headsets is far better than that using Neurosky headsets, as there are lots of mix-ups in the Neurosky data between different classes. This is reasonable since the former has seven channels and the latter has only one channel.

5 Discussion

In this paper, we compare different classifiers in classifying EEG data collected from different brain states. In the beginning, we base our classifiers using spectral amplitude contents of EEG beta. Supervised machine learning classifiers perform much better than unsupervised learning classifiers.

We also notice that, with increasing number of subjects in the training data, the misclassification rate may or may not go down. However, increasing the size of the training set obtained from the same subject, the misclassification rates, especially misclassification for support vector machines, go down significantly. Compared to other works that tried to identify differences between different brain states or emotion situations, we can deal with larger data sets [11, 15]. Also, we used R in all our classifications. And since R can be implanted into Neurosky headset systems, we anticipate that with a self-adaptive system, our classifiers will have very low misclassification rates identifying differences between gaming and idle two brain states. Our experiments also show that performance of classifiers is related to the training data set. Sometimes tree-based methods have better classification results; sometimes other distance based methods work better. Majority vote, which combines all the result together, may or may not give the smallest misclassification rate for a single case. However, it is stable in general.

Other studies have shown that different methods in studying brain help improving childrens study[2], and

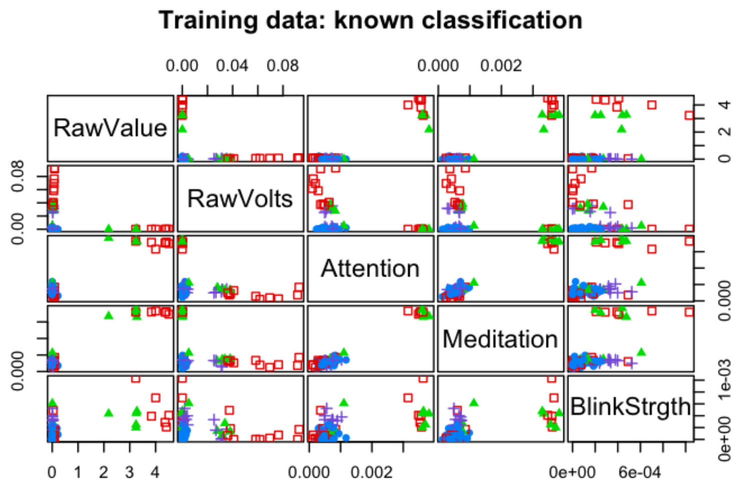

Figure 6: Scatter Plot of Sample Entropy (Collected using Neurosky Headset)

(Explanation: blue dots: idle; purple cross: gaming; red diamond: idle to gaming; gree triangle: gaming to idle. Variables are raw data reported by Neurosky headset)

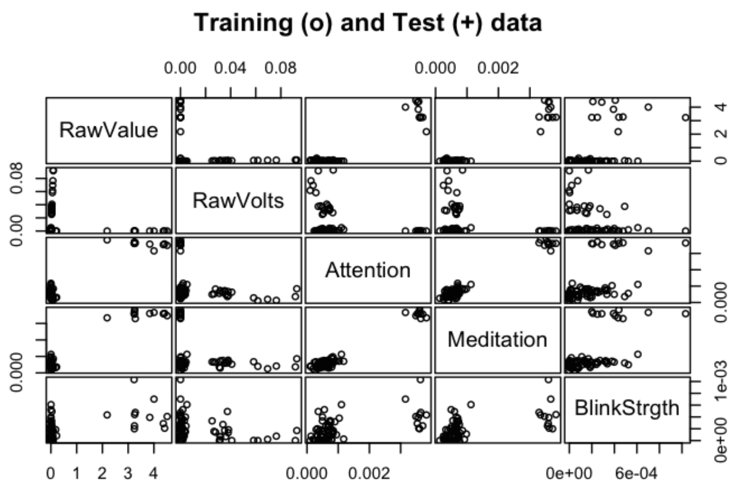

Figure 7: Scatter Plot of Sample Entropy (Collected using Neurosky Headset)

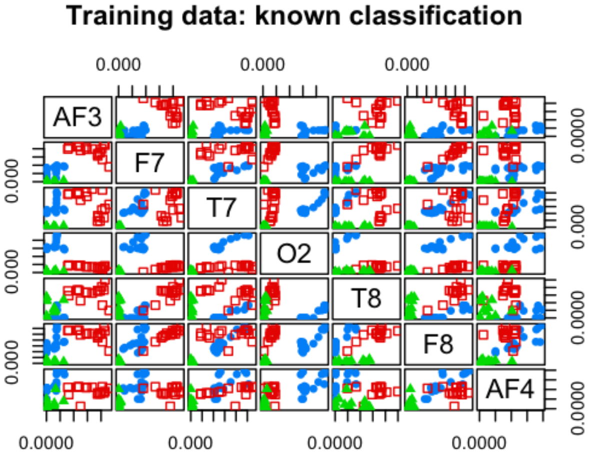

Figure 8: Scatter Plot of Sample Entropy (Collected using Emotiv Headset)

(Explanation: blue dots: talking; red diamond: idle; gree triangle: meditation. 7 variables are 7 different channel's name, and raw values reported by Emotiv headset.)

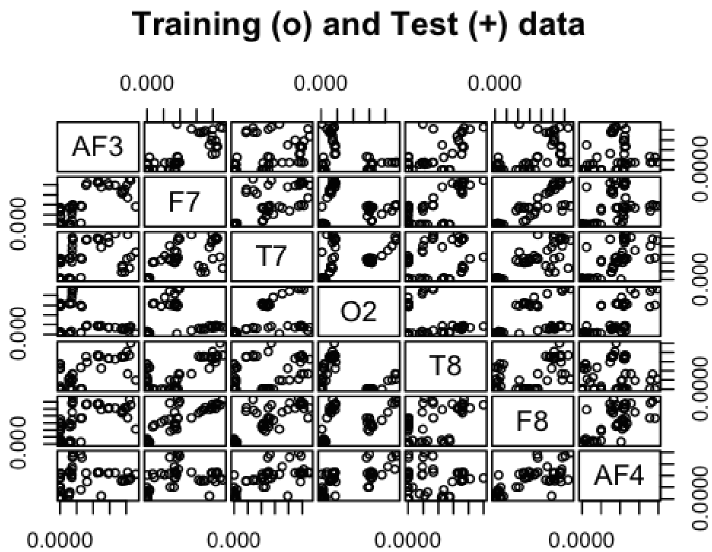

Figure 9: Scatter Plot of Sample Entropy (Collected using Emotiv Headset)

Table 6: Classification Neurosky Data Sample Entropy

Tree Bagging		Predicted States			
		0	1	2	3
True	0	9	0	0	0
	1	1	5	3	0
	2	2	0	4	2
	3	2	2	1	4

Gaussian Mixture Model		Predicted States			
		0	1	2	3
True	0	8	0	1	1
	1	1	5	3	0
	2	2	1	4	1
	3	2	1	5	1

Boost		Predicted States			
		0	1	2	3
True	0	7	1	1	0
	1	1	4	3	1
	2	1	2	3	2
	3	2	3	1	3

Support Vector Machine		Predicted States			
		0	1	2	3
True	0	9	0	0	0
	1	1	4	4	0
	2	2	1	5	0
	3	4	0	4	1

Majority Vote		Predicted States			
		0	1	2	3
True	0	9	0	0	0
	1	1	5	3	0
	2	3	1	3	1
	3	2	1	2	4

0: idle; 1: gaming; 2: idle to gaming; 3: gaming to idle

we intend to use our study to help people bring their brain does give the smallest misclassification rate between active to inactive states, and thus better sleep. Compared to other studies, data mining algorithms here are closer to being black boxes, and thus possibly be more flexible.

Previous research shows that sample entropy is helpful in the diagnosis of pathological conditions, such as epilepsy or other seizures [16, 8]. Here, we demonstrate that sample entropy is also a good tool to identifying changes in brain states. Adding extra channels also helps identify differences, as classification results based on seven channels is better than classification results based on one channel.

Table 7: Classification of Emotiv Data Sample Entropy

Tree Bagging		Predicted States		
		idle	meditation	talking
True	idle	5	0	0
	meditation	0	5	0
	talking	0	0	5

Gaussian Mixture		Predicted States		
		idle	meditation	talking
True	idle	5	0	0
	meditation	0	5	0
	talking	0	0	5

Boost		Predicted States		
		idle	meditation	talking
True	idle	5	0	0
	meditation	0	5	0
	talking	0	0	5

SVM		Predicted States		
		idle	meditation	talking
True	idle	5	0	0
	meditation	0	5	0
	talking	0	0	5

Majority Vote		Predicted States		
		idle	meditation	talking
True	idle	5	0	0
	meditation	0	5	0
	talking	0	0	5

6 Conclusions & Future Work

From our previous sections, we conclude that for different data sets, different models have different performances. We conclude that majority vote, though maybe not the best classifier for each situation, is the safest way to do a classification in general. By increasing the number of subjects and increasing the training data size, the misclassification rates decrease. Also, unsupervised machine learning is not a good method here, since k-means could barely tell the difference between 2 different brain states.

Sample entropy works well. This suggests that brains in different states have different uncertainty patterns, and entropy is a good tool to identify the differences.

Part of our future work will be to test different types of non-intrusive EEG headsets, preferably which have more than one channel. We are also aiming at building an online self-adaptive system where users can upload their data so that they can build a classifier that is the most suitable for their brain states.

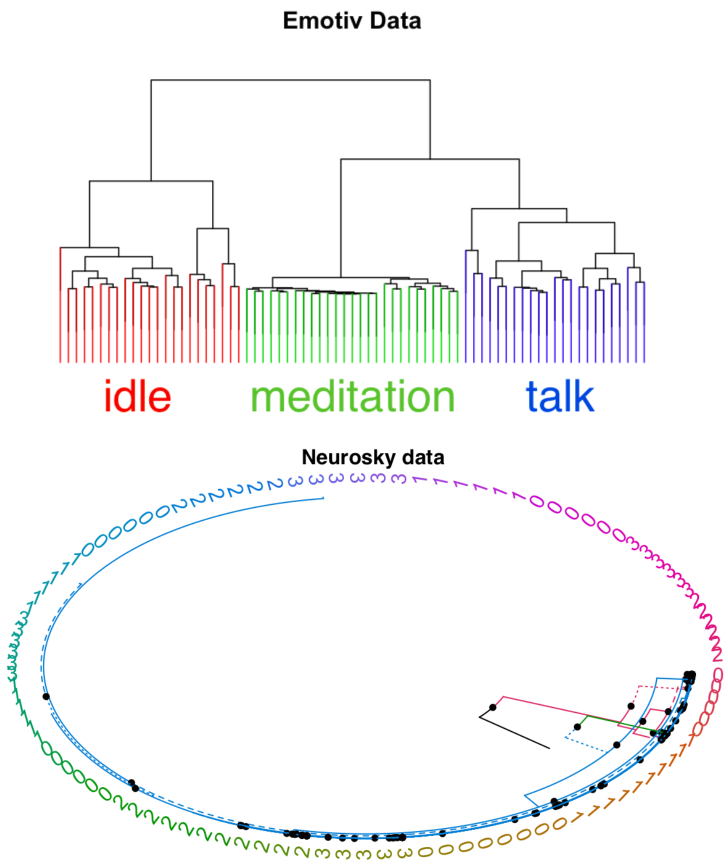

Figure 10: Hierarchy Clustering for Sample Entropy

(Explanation: 0: idle; 1: game; 2: idle to game; 3: game to idle)

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AUTHOR BIOGRAPHIES

Yuezhe Li received her B.S. degree in Statistics from Huazhong University of Science and Technology in China. She is now pursuing her M.S. degree in Mathematics in Illinois State University. Her internship in Blue Waters Student Internship is mentored by Dr. Hong Lin working on Dynamic Modeling of EEG Data from Brain State Intelligence and Cognitive Health.

Dr. Yuchou Chang is an assistant professor at Computer Science and Engineering Technology Department, University of Houston - Downtown. He received his B.E., M.E., and Ph.D. from Northwestern Polytechnical University (China), Shanghai Jiao Tong University (China), and University of Wisconsin - Milwaukee, respectively. He also received his post-doc training at Barrow Neurological Institute. His research interests include biomedical devices, signal acquisition and processing, EEG, MRI, computer vision, and machine learning

Dr. Hong Lin received his Ph.D. degree in Computer Software from University of Science and Technology of China. Dr. Hong Lin was a postdoctoral research associate at Purdue University; an assistant research officer at the National Research Council, Canada, and a software engineer at Nokia, Inc. Dr. Lin is currently a professor with University of Houston - Downtown. His research interests include computational neurology, parallel/distributed computing, grid computing, multi-agent systems, and high level computational models. He is a co-supervisor of the Grid Computing Lab at University of Houston - Downtown.