Classification of Conscious States with EEG Analysis

Yi-Hsiu Lin, Yi-Xuan Lai
National Yang Ming Chiao Tung University, Department of Computer Science

ABSTRACT

During the class, Professor Yan introduced us to various applications of biomedical signals. Among them, we were particularly interested in the application of EEG for detecting the sleep state of drivers to prevent accidents. Therefore, we aimed to explore this application, especially focusing on the method of feature extraction.

We reviewed relevant papers on EEG signal processing and designed an experiment for our project. We implemented and compared four feature extraction methods using an SVM classifier: standard statistics, Short-Time Fourier Transform (STFT), Vector Autoregressive (VAR), and Power Spectral Density (PSD). Additionally, we experimented with various window sizes and lags to determine the optimal parameters for our analysis. Our results indicate that the Short-Time Fourier Transform (STFT) method achieved the highest accuracy, whereas the Vector Autoregressive (VAR) model had the lowest accuracy.

1. Introduction

1.1 Electroencephalography

Electroencephalography (EEG) records the electrical activity of the brain and is widely used in various biomedical applications, including sleep state detection. EEG signals are characterized by different frequency bands, each associated with specific mental states:

- Delta (0.5-4 Hz): Dominant during deep, dreamless sleep.
- Theta (4-8 Hz): Associated with deep relaxation and drowsiness.
- Alpha (8-13 Hz): Present during relaxed, awake states, especially with eyes closed.
- Beta (13-30 Hz): Indicative of active thinking, focus, and alertness.
- Gamma (30 Hz and above): Linked to higher cognitive functions and intense mental activity.

These waveforms are crucial for analyzing EEG data to detect and interpret different sleep states and other cognitive conditions.

1.2 Motivation of the study

Our motivation stems from Professor Yan's lecture, where he mentioned using EEG to detect if a driver is dozing off, thereby preventing car accidents. We found this application very meaningful and decided to explore this field to see if specific patterns in EEG can be used to assess the driver's state of consciousness.

Unlike existing studies, our experiment focuses on discussing the impact of different feature extraction methods on the overall classification model. We aim to understand various signal processing techniques and compare the effectiveness of these methods through this process. Such a comparison is not commonly seen in current studies.

2. Related work

2.1 Mental attention state classification

A study done on Kaggle[1] investigates changes in mental states during tasks requiring sustained attention, such as monitoring automated systems or piloting in autopilot mode. EEG data from five participants operating a Microsoft train simulator were collected over five sessions. Feature extraction utilized Short-Time Fourier Transform (STFT) with a Blackman window for noise suppression. Classification employed Support Vector Machine (SVM), achieving up to 97% accuracy in identifying attention states. Results suggest that EEG activity in frontal and parietal lobes, particularly in 1-5 Hz and 10-15 Hz frequency bands, correlates with attention states.

2.2 Signal processing techniques

Our implementation references the paper "Signal Processing Techniques Applied to Human Sleep EEG Signals—A Review[2]." The overview presents a diverse array of methods for analyzing sleep EEG signals. This article offers a comprehensive overview of these methods and provides guidance for selecting appropriate signal processing techniques. It focuses on three key stages: pre-processing, feature extraction, and feature classification. Pre-processing techniques prepare the sleep EEG signal for further analysis, while feature extraction and classification methods characterize and classify the signals. Performance criteria are provided where applicable. Supplementary materials include taxonomy tables and categorizations based on applications in sleep staging, transient pattern detection, and sleep-disordered breathing diagnosis.

3. Material and methods

3.1 Dataset

We downloaded the dataset from Kaggle - EEG Data for Mental Attention State Detection. It comprises 34 experiments monitoring the attention state of human subjects using passive EEG BCI with 25 channels and a sampling frequency of 128 Hz. Each EEG data file is stored in Matlab format and split into three time-based classes: focused, unfocused, and drowsed.

Fig. 1. provides a glimpse of the visualized dataset in waveform.

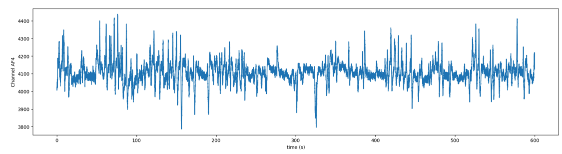
3.2. Experiment Design

Our experiment consists of several steps. First, we perform data cleaning to exclude unnecessary data and retain useful channels. Next, in the data preparation phase, we split the EEG data into three states based on time and repackage the dataset to suit the Subject-Specific paradigm. Following this, we move to feature extraction, which is the focus of our experiment. We experimented with four different feature extraction methods, which will be detailed in *Section 3.4*, and then proceed to classification. Finally, we analyze the results and discuss the overall findings of the study. The process is shown in Fig. 2.

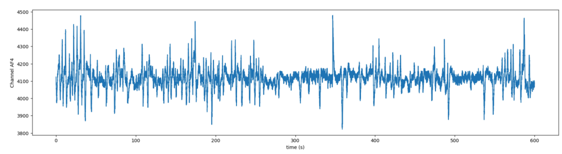
3.3. Data analysis

3.3.1 Lag plot

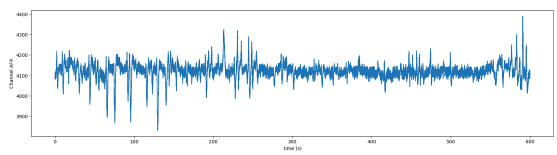
A lag plot is a graphical method used to check for autocorrelation in time series data. It plots the current observation against the previous observation at a specific lag interval. This helps visualize whether there is a relationship between observations at different time points, indicating potential patterns or dependencies in the data.



(a) Focused



(b) Unfocused



(c) Drowsed

Fig. 1. Visualization of Subject #1, the third experiment, and the AF4 channel in (a) Focused, (b) Unfocused, and (c) Drowsed states.

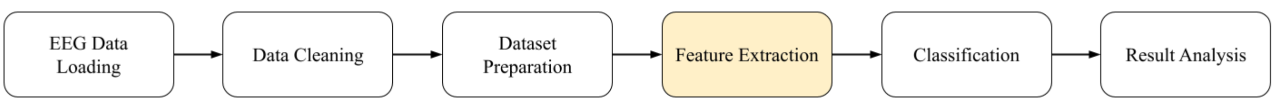


Fig. 2. Flowchart of the experiment.

In our study, scatter plots were created to visualize lag effects at lag intervals of 1, 3, 5, 7, and 9. It is evident that as the lag time increases, the distribution of points becomes more scattered. This is represented by the appearance of thicker diagonal lines in the plots, indicating lower correlation between the respective time points. Therefore, for the third feature extraction method (VAR), we opted for the shortest lag parameter of 1.

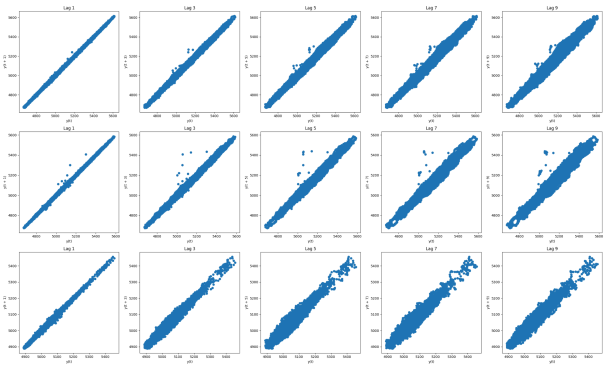


Fig. 3. Lag plot of EEG signals: from top to bottom - focused, unfocused, drowsed states; from left to right - lag intervals 1, 3, 5, 7, 9.

3.3.2 ADF test

The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine whether a unit root is present in a time series dataset. It assesses whether a given time series is stationary or non-stationary. A stationary time series has constant mean and variance over time, while a non-stationary one does not. The ADF test helps in understanding the long-term behavior of a time series, making it a crucial tool in time series analysis and forecasting.

In our EEG dataset, across all three categories (focused, unfocused, drowsed), the results consistently demonstrate stationarity. This finding underscores the stability of EEG signals within each category over time.

3.4. Feature extraction

3.4.1 Standard Statistics

Here we concatenate standard deviation, skewness, and kurtosis.

In EEG data analysis, standard deviation reflects the signal's fluctuation over a period, indicating specific brain activities. Skewness and kurtosis are also essential metrics. Since real-world data often deviate from a normal distribution, skewness measures the asymmetry of data distribution, while kurtosis indicates the sharpness or peakedness relative to a normal distribution. Together, skewness and kurtosis help us understand the shape and characteristics of data distributions.

3.4.2 Short-time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) is a technique used to analyze the frequency content of non-stationary signals, such as EEG data, over time. By segmenting the signal into overlapping windows and applying the Fourier Transform to each segment, STFT provides a time-frequency representation of the signal. This allows for the examination of how the spectral content evolves over time, making it a powerful tool for identifying patterns and changes in EEG signals.

3.4.3 Vector Autoregressive (VAR)

The Vector Autoregressive (VAR) model is a statistical model used to capture the linear interdependencies among multiple time series. In the context of EEG analysis, VAR can model the relationship between different EEG channels over time, allowing for the prediction of future values based on past observations. This makes it useful for understanding the dynamic interactions within the brain and for forecasting EEG signal trends.

3.4.4 Power Spectral Density (PSD)

Power Spectral Density (PSD) is a measure used in signal processing to describe the distribution of power into frequency components in a signal. In the context of EEG analysis, PSD provides valuable insights into the frequency content of brain activity. By calculating the PSD of EEG signals, researchers can identify dominant frequency bands associated with different mental states, such as relaxation, attention, or sleep stages. PSD analysis helps uncover patterns and changes in brain activity over time, aiding in the interpretation of EEG data in various applications, from cognitive neuroscience to clinical diagnostics.

4. Results

In this section, we present our experiment results from two aspects. First, we compare the accuracy rates of five subjects using four different feature extraction methods. Second, we compare the performance differences across seven window sizes.

4.1 Overall comparison

Since we adopted the Subject-Specific paradigm, a separate model is trained for each subject's data. The results shown in Fig. 4. and Table 1. include data from five subjects, displaying the accuracy achieved using four different feature extraction methods.

Although the results vary for each subject, a general trend can be observed. The STFT method yields the best performance, achieving nearly 100% accuracy. The second-best method is PSD, followed by Statistical Analysis, while the VAR method has the lowest accuracy, with only about 50-60%.

4.2 Window sizes comparison

To investigate how different window sizes affect the model's performance, we randomly selected data from two subjects for testing and experimented with window sizes of 1, 5, 8, 12, 15, 20, and 24 seconds.

As shown in Fig. 5, as the window size increases, the performance of each method improves consistently, except for the STFT (orange line), which is already close to 100%, leaving little room for significant improvement.

5. Discussion

In this section, we have discussed several questions based on our observations of the experiment results.

5.1. Why is the Subject-Specific paradigm better?

In fact, we did not conduct this experiment ourselves but based our conclusions on the results from the paper. However, the paper does not explain the actual reason why the Subject-Specific paradigm yields better results than the Common-Subject paradigm.

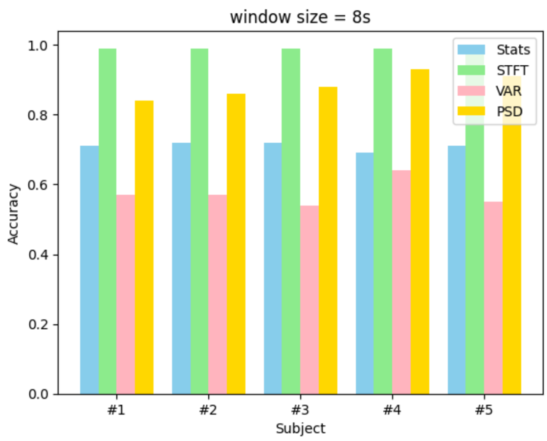


Fig. 4. The testing accuracy for all subjects using different feature extraction methods.

	#1	#2	#3	#4	#5
Stats	0.71	0.72	0.73	0.68	0.70
STFT	0.98	0.98	0.98	0.99	0.98
VAR	0.56	0.58	0.54	0.62	0.54
PSD	0.84	0.85	0.86	0.93	0.89

Table 1. The average accuracy of 5-fold cross-validation for the training dataset. Note that the highest scores are shown in red.

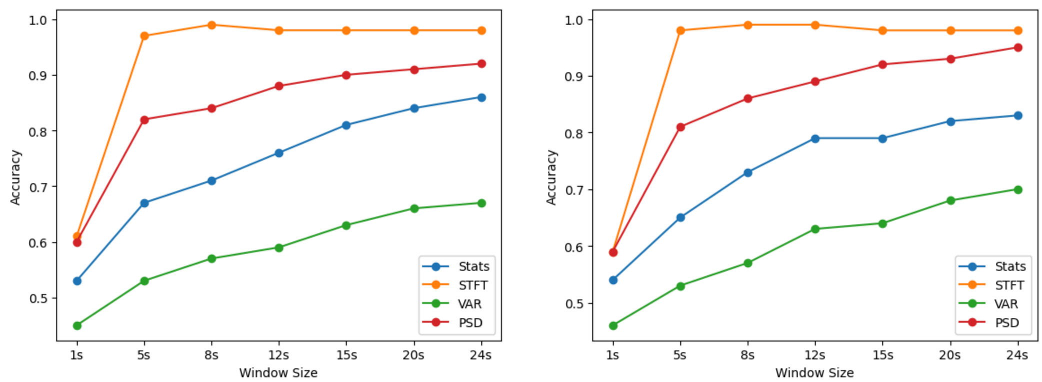


Fig. 5. Line charts showing accuracy for different window sizes.

Our hypothesis is that each person's brain waves may have minor individual differences due to personal physiological and neural system variations. Therefore, training the model with each individual's biosignals will provide better performance than training with general data.

5.2. How does window size affect performance?

On one hand, if the window size is too large, sudden frequency values cannot be detected; on the other hand, if the window size is too small, it may fail to capture representative features within a short time and become too sensitive to frequency changes. So how should we choose the appropriate window size? From our review of the papers, the conclusion is that there is no general rule; it varies depending on the case, and multiple attempts are necessary to find the appropriate size.

According to the papers we referenced, most studies test window sizes ranging from a few seconds to over ten seconds. Based on the line charts we previously presented, the accuracy in our experiment continues to increase up to 24 seconds.

5.3. How did we determine the window size?

We first determined a testing interval of 1 second to over 20 seconds, which is slightly larger than the range used in the referenced papers. Based on the test results, the window size that performed best with most of the data is 24 seconds.

However, as Professor Chen pointed out, 24 seconds is not sufficient for making adequate safety responses while driving, so we finally chose a more practical 8 seconds.

5.4. Performance comparison of the four feature extraction methods?

Among them, the Short-Time Fourier Transform (STFT) performed the best because it can capture signal variations in both the time and frequency domains. EEG activities exhibit specific dynamic characteristics within different frequency ranges, and STFT can effectively capture these dynamics and event-related information.

On the other hand, Vector Autoregression (VAR) requires estimating numerous parameters, making it more challenging when the signal dimensions are high or the data is limited, thereby affecting overall accuracy and generalization ability, given our relatively small dataset.

5.5. What may be our future improvements?

Firstly, we used the same window size when comparing various feature extraction methods this time. However, it can be observed from the earlier line graph that not all methods perform best at the same window size. Therefore, it is necessary to set a suitable window size for each method, which is also one of the shortcomings of our experiment this time.

Secondly, we can explore the use of neural networks for signal classification, particularly models with time-series properties like LSTM. There might be a chance to achieve better results. However, as Professor Zeng mentioned, our dataset is too small, and using deep learning models might not necessarily yield better results. Therefore, if we want to pursue this approach, we may need to augment our dataset first.

Thirdly, Professor Chen suggested that we could adopt the current trend of multimodal models. We can consider integrating other biosignals for a comprehensive evaluation, such as breathing and eye-tracking.

6. Conclusions

In this study, we used EEG data to classify the conscious states of drivers and explored the impact of different feature extraction methods using various window sizes. Among them, STFT performed the best due to its ability to capture signal variations in both the time and frequency domains. In our case, larger window sizes generally yielded better results, but considering practical factors, we ultimately chose 8 seconds as the appropriate window size.

This field already has several real-world applications. For instance, Ford designed an EEG helmet for race car drivers that monitors their brainwaves to help them stay focused and perform their best. Impecca released a product called 'Alert Band,' which uses a circular EEG sensor worn on the driver's head to measure their fatigue level. Last year, a new product called M.Brain was introduced. It is an EEG detector in the form of an earphone that monitors brain waves around the ears to provide real-time monitoring of the driver's mental state. Its lightweight design is one of its key features.

In light of the success of these real-world cases, we believe that our experimental results contribute to this field and may one day be put into practice!

References

[1] C.I. Acı, M. Kaya, Y. Mishchenko, Distinguishing mental attention states of humans via an EEG-based passive BCI using Machine Learning Methods, Expert Systems with Applications, vol. 134, pp. 153-166, 2019.

[2] Shayan Motamedi-Fakhr, Mohamed Moshrefi-Torbati, Martyn Hill, Catherine M. Hill, Paul R. White, Signal processing techniques applied to human sleep EEG signals—A review, Biomedical Signal Processing and Control, Volume 10, 2014, Pages 21-33, ISSN 1746-8094