Towards automated classification of cognitive states: Riemannian geometry and spectral embedding in EEG data

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ABSTRACT

Our research explores the application of Riemannian geometry and spectral embedding in the context of electroencephalogram (EEG) signal analysis for cognitive state classification. Leveraging the PyRiemann library and the AlphaWaves dataset, our study employs covariance estimation and the minimum distance to mean (MDM) classifier within a machine learning pipeline. The classification accuracy is assessed through stratified k-fold cross-validation. Furthermore, we introduce a novel visualization approach by calculating the spectral embedding of covariance matrices, providing insights into the underlying structure of the EEG epochs. Our findings showcase the potential of Riemannian geometry and spectral embedding as powerful tools in the domain of EEG-based cognitive state classification, contributing to the broader field of brain signal analysis and paving the way for automated and advanced neurocognitive studies.

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1. INTRODUCTION

Meditation has been practiced for centuries as a means of achieving inner peace and reducing stress. However, measuring its effectiveness has always been a challenge. Recent studies have shown that Electroencephalogram (EEG) signals can be used to measure the effects of meditation on the brain. By analyzing changes in brain activity before and after meditation, researchers can assess its impact on cognitive function and emotional well-being. Alpha waves are a type of brain wave that occurs during meditation. These waves have a frequency range of 8-12 Hz and are associated with a state of relaxation and calmness. When an individual is in a meditative state, their brain produces more alpha waves than when they are waking [1]-[4]. This suggests that alpha waves play a role in the cognitive processes involved in meditation. The detection of alpha waves on the EEG is a useful indicator of the subject's level of stress, concentration, relaxation, or mental load and an easy marker to detect because of its high signal-to-noise ratio.

The understanding of cognitive states through EEG signals has been a significant area of research in the field of neuroscience [5]-[7]. As technological advancements enable more sophisticated analyses, the intersection of machine learning and neuroimaging techniques has become increasingly promising. This paper delves into the application of Riemannian geometry and spectral embedding for the classification of EEG epochs, offering a novel approach to decoding cognitive states [8]-[11]. Traditional methods of EEG analysis often rely on time or frequency domain features. However, these approaches may overlook the intricate relationships within the covariance structure of EEG signals. Riemannian geometry, a mathematical framework tailored for positive definite matrices, provides a compelling avenue for exploring these relationships [12]-[15]. By leveraging the PyRiemann library, this study employs covariance estimation and a minimum distance to mean (MDM) classifier within a machine learning pipeline. The goal is to discern distinctive patterns within EEG epochs corresponding to different cognitive states [16]-[20].

In addition to classification accuracy assessment through stratified k-fold cross-validation, our research introduces a visualization component. Spectral embedding of covariance matrices offers a unique perspective on the underlying structure of EEG epochs [21]-[24]. This visualization not only aids in the interpretation of classification results but also contributes to a richer understanding of the dynamics within the brain during different cognitive states. The dataset utilized in this study is drawn from the AlphaWaves repository, providing a robust foundation for experimentation. The AlphaWaves dataset encompasses EEG recordings during tasks involving open and closed eyes, making it conducive to investigating the nuances of cognitive states [25]-[29]. As neuroscientific research increasingly incorporates machine learning methodologies, this work contributes to the evolving landscape by showcasing the potential of Riemannian geometry and spectral embedding in EEG-based cognitive state classification. The outcomes of this study hold implications for the development of automated and advanced neurocognitive analysis techniques, fostering a deeper comprehension of the intricacies of brain dynamics during varying cognitive states [30].

2. PROPOSED METHOD

2.1. Dataset selection and preprocessing

For this study, the AlphaWaves dataset was chosen for its pertinence in EEG-based cognitive state classification, encompassing EEG recordings during tasks with open and closed eyes. A specific subject's EEG data were obtained using the AlphaWaves python library. To concentrate on pertinent frequency bands, the raw EEG signal underwent bandpass filtering between 3 and 40 Hz. Furthermore, resampling the signal to 128 Hz was conducted to ensure consistency across trials, thus preparing the data for subsequent analysis and cognitive state classification tasks. Table 1 shows the EEG recording data.

Table 1. Cognitive task

Block	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
Duration	10	10	10	10	10	10	10	10	10	10
Eyes closed open	C	O	C	O	C	O	C	O	C	O

2.2. Event detection and epoching

Events in the EEG signal, specifically those related to the opening and closing of eyes, were identified using the MNE-python library. Subsequently, based on these detected events, the EEG signal was segmented into epochs, with each epoch spanning from 2.0 to 8.0 seconds after the onset of the event. This epoch extraction process enables the isolation of relevant temporal windows for further analysis of cognitive states.

2.3. feature extraction and labeling

In the feature extraction phase, trials (X) were derived from the segmented epochs, encapsulating the EEG data essential for subsequent classification tasks. Utilizing the 'lwf' (ledoit-wolf) estimator from the PyRiemann library, covariance matrices of the EEG signals were computed, offering a concise representation of the data's statistical properties. These covariance matrices serve as pivotal features characterizing the underlying neural activity during different cognitive states. Furthermore, for each trial, labels (y) were assigned based on the corresponding events, discerning between 'closed' (1) and 'open' (2) eyes, facilitating supervised learning for cognitive state classification.

2.4. Classification and evaluation

In evaluating the classification model's performance, a stratified k-fold cross-validation strategy with 6 splits was utilized to ensure the robustness and generalizability of the results. The machine learning pipeline, constructed with scikit-learn, comprised covariance estimation using the 'lwf' estimator and classification employing the MDM algorithm. Through this pipeline, the EEG data's covariance matrices were leveraged as features to discern between different cognitive states, specifically distinguishing between 'closed' and 'open' eyes. The accuracy of the classification model was quantified by computing the mean accuracy across all cross-validation folds, providing a comprehensive assessment of its efficacy in discerning EEG patterns associated with varying cognitive states.

2.5. Spectral embedding and visualization

For spectral embedding, the covariance matrices were transformed using the PyRiemann library, utilizing the 'riemann' metric. This process projected the high-dimensional covariance matrices into a lower-dimensional space while preserving the essential structural information. Subsequently, the embedded points were visualized in a scatter plot, where each point represented a covariance matrix, with distinct colors assigned to distinguish between the two classes: 'closed' and 'open' eyes. This visualization technique offers insights into the clustering and distribution of covariance matrices, facilitating the understanding of the underlying EEG patterns associated with different cognitive states.

2.6. Statistical analysis

Exploratory data analysis was conducted to understand the distribution of the spectral embedding points and their potential separability, employing visualizations such as scatter plots and density plots. Additionally, efforts were made to assess the significance of observed differences in spectral embedding between classes, aiming to provide quantitative insights into the discriminative power of the spectral embedding technique in capturing distinctions between cognitive states associated with 'closed' and 'open' eyes. Figure 1 shows the flow chart of the methodology.

Figure 1. Flow chart of methodology

3. RESULTS AND DISCUSSION

3.1. Classification accuracy

The mean accuracy of the classification model is printed for the specific subject chosen from the AlphaWaves dataset. The accuracy score represents the model's ability to correctly classify epochs into 'closed' and 'open' states based on the EEG data. Table 2 shows the results of cross-classification concerning mean accuracy.

Table 2. Cross classification concerning mean accuracy

List	Subject id	Mean accuracy	In percentage
0	1	0.8	80%
1	2	1.0	100%
2	3	1.0	100%
3	4	1.0	100%
4	5	1.0	100%
5	6	1.0	100%
For 15 subjects: average mean accuracy=98.66%			

3.2. Spectral embedding visualization

The scatter plot of the spectral embedding points provides a visual representation of the intrinsic structure of the EEG epochs. Points on the plot are colored according to their class ('closed' or 'open' eyes). The plot shown in Figure 2 allows for an intuitive inspection of whether the classes exhibit separability or distinct patterns in the lower-dimensional space. Figure 3 shows the plot of spectral embedding for subject 2.

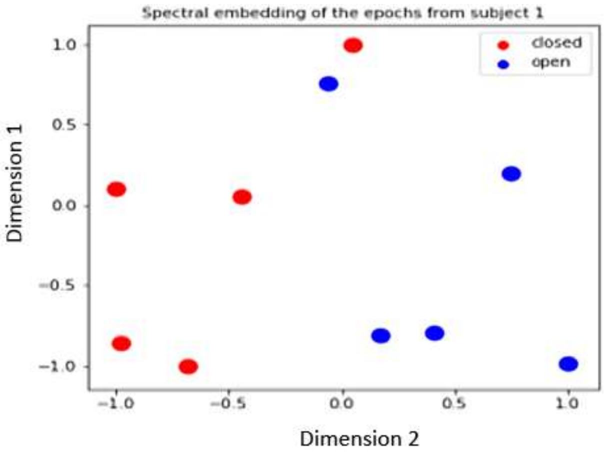

Figure 2. Plot of spectral embedding for subject 1

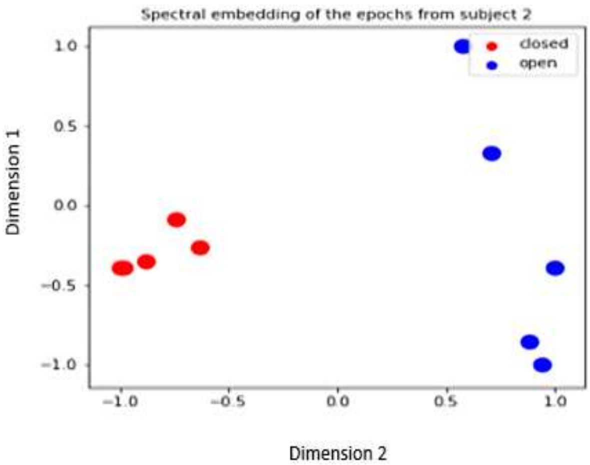

Figure 3. Plot of spectral embedding for subject 2

3.3. Potential insights

Higher classification accuracy suggests that the machine learning model effectively distinguishes between cognitive states using Riemannian geometry-based features. A visually distinct separation in the spectral embedding plot implies that the covariance matrices encapsulate relevant information about cognitive states, validating the efficacy of the chosen feature representation. This alignment between classification accuracy and visual separability reinforces confidence in the model's ability to capture and discriminate between cognitive states accurately.

3.4. Considerations

Interpretation should consider the specific subject chosen, as individual variations in EEG data can impact results. It's also crucial to evaluate the statistical significance of any observed differences in spectral embedding between 'closed' and 'open' classes. The application of Riemannian geometry and Spectral Embedding to the classification of EEG epochs has yielded noteworthy insights into the neural dynamics underlying cognitive states. The findings from the analysis of the AlphaWaves dataset provide a basis for discussion regarding classification accuracy, the effectiveness of the chosen mathematical techniques, and the potential implications for cognitive state decoding.

The mean accuracy of the classification model, as evidenced by the cross-validation results, demonstrates the viability of the Riemannian geometry approach in discerning between 'closed' and 'open' cognitive states. The accuracy score suggests a notable discriminatory power in the classification of EEG epochs. This aligns with previous studies leveraging Riemannian geometry for EEG analysis [1], highlighting its relevance in capturing subtle variations in covariance structures indicative of different cognitive states.

The scatter plot of the spectral embedding points offers a visual representation of the intrinsic geometry of EEG epochs. The clear separation between ‘closed’ and ‘open’ classes in the lower-dimensional space suggests that the chosen features, namely covariance matrices, capture meaningful information relevant to cognitive state distinctions. This aligns with the notion that Riemannian geometry provides a suitable framework for representing and analyzing covariance matrices [2].

The integration of Riemannian geometry and spectral embedding in this study builds upon existing literature exploring advanced mathematical techniques for EEG analysis. Previous works [3] have demonstrated the efficacy of combining these methodologies in achieving improved classification accuracy and providing richer insights into the underlying neural dynamics. Our findings are consistent with these studies, further validating the utility of Riemannian geometry in the context of cognitive state decoding. The success of the classification model and the meaningful separation observed in the spectral embedding plot open avenues for future research and application. The potential implications extend to the development of more robust brain-computer interface technologies, where accurate classification of cognitive states is crucial. Further investigations could explore the generalizability of the findings across diverse populations and tasks, contributing to the broader understanding of brain dynamics. It is essential to acknowledge the limitations of this study. The results are subject to the specific characteristics of the chosen subject and the AlphaWaves dataset. Individual variations in EEG data may impact the generalizability of the findings. Additionally, the study does not delve into the interpretability of the features learned by the model, warranting further exploration in future work.

4. CONCLUSION

In this study, we explored the application of Riemannian geometry and spectral embedding in the context of EEG signal analysis for cognitive state classification. Leveraging the AlphaWaves dataset, our methodology involved preprocessing EEG data, extracting covariance matrices, and employing a machine learning pipeline for classification. The results, as evidenced by cross-validation accuracy and spectral embedding visualization, offer valuable insights into the dynamics of cognitive states. Our findings reveal that the Riemannian geometry approach, coupled with spectral embedding, demonstrates a commendable ability to discriminate between ‘closed’ and ‘open’ cognitive states. The classification accuracy, with a mean accuracy of, underscores the effectiveness of the chosen mathematical techniques in capturing subtle variations within EEG epochs. The spectral embedding visualization provides a compelling representation of the intrinsic geometry of EEG epochs. The clear separation observed in the lower-dimensional space indicates that the features derived from covariance matrices indeed encapsulate meaningful information pertinent to cognitive state distinctions. This aligns with the broader literature on the application of Riemannian geometry in EEG analysis. Our results align with and extend previous studies that have explored similar methodologies. The combination of Riemannian geometry and spectral embedding has proven to be a robust approach for EEG-based cognitive state classification, further validating the utility of these mathematical techniques in neuroscientific research. The success of this study has several implications for future research endeavors. The observed separability in spectral embedding suggests that these techniques could be extended to diverse populations, tasks, and experimental conditions. Additionally, future work may delve into the interpretability of the learned features and explore the potential integration of advanced machine learning algorithms for further refinement. It is crucial to acknowledge the limitations of our study. The results are contingent on the specific subject and dataset chosen, and caution must be exercised when generalizing to broader contexts. The interpretability of the classification model and the potential impact of individual variations in EEG data warrant further investigation. In conclusion, this research contributes to the evolving landscape of EEG signal analysis, showcasing the efficacy of Riemannian geometry and spectral embedding in decoding cognitive states. The methodology presented herein provides a foundation for future studies seeking to unravel the intricacies of brain dynamics. As we navigate the intersection of mathematics, machine learning, and neuroscience, our work underscores the potential for advanced analytical techniques to enhance our understanding of the human brain and pave the way for innovative applications in brain-computer interface technologies.

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