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Machine Learning-Based Comparison of EEG Signals During Associative Equivalence Learning with Visual Stimuli of Varying Complexity

Summary of PhD Thesis

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List of publications related to the subject of the thesis

1. Á. Kiss, K. Tót, N. Harcsa-Pintér, *et al.*, "Machine learning analysis of cortical activity in visual associative learning tasks with differing stimulus complexity," *Physiology International*, 2025, ISSN: 2498-602X. [Online]. Available: `https://m2.mtmt.hu/api/publication/35759496`

2. Á. Kiss, O. M. Huszár, B. Bodosi, *et al.*, "Automated preprocessing of 64 channel electroenchephalograms recorded by biosemi instruments," *MethodsX*, vol. 11, p. 102 378, Dec. 2023, ISSN: 2215-0161. DOI: `10.1016/j.mex.2023.102378`. [Online]. Available: `http://dx.doi.org/10.1016/j.mex.2023.102378`

1 Abstract

This thesis explores the neural basis of associative learning using EEG and machine learning. It compares the standard Rutgers Acquired Equivalence Test (RAET) with a simplified version, Polygon, to determine how stimulus complexity affects learning. EEG data were processed with Independent Component Analysis and analyzed using LSTM networks and Support Vector Classification across key brain regions. Findings reveal that the frontal lobe is most sensitive to differences between the tasks, while the parietal lobe shows minimal change. Despite a limited sample, the study highlights the potential of these techniques to deepen our understanding of cognitive processes.

List of abbreviations

EEG Electroencephalography

fMRI Functional Magnetic Resonance Imaging

ICA Independent Component Analysis

LSTM Long Short-Term Memory

ML Machine Learning

RAET Rutgers Acquired Equivalence Test

SVC Support Vector Classification

2 Introduction

Associative learning enables organisms to anticipate events and respond to stimuli, aiding adaptation. This thesis focuses on acquired equivalence learning, where chains of associations merge into larger groups. Early work by Catherine Mayers and colleagues at Rutgers, using fish and face stimuli, utilized a transfer (or generalization) step - later termed RAET[1] test. Their findings suggest that hippocampal function is crucial for the transfer part of associative learning, with notable differences observed between healthy and Parkinson's patients.

The question about which parts of the brain are involved in equivalence learning, recalling, or retrieving steps is axiomatic, although the answer is complex.

fMRI[2] results indicate that both the Medial Temporal Lobe and Caudate Nucleus are active in associative tasks, while EEG[3] findings link attention and decision-making – particularly in Brodmann area 11 – to learning performance. Additionally, the complexity of visual stimuli influences learning, as richer cues or easier verbalization can engage more complex brain processes. To address this, variants of the RAET test, such as the Polygon have been developed.

The RAET and most RAET-like tests contain two main phases. The first is often called learning or acquisition, while the succeeding is labeled as the test phase. The test phase is the mixture of so-called retrieval and generalization tasks. During the retrieval, the explicit memory is measured with associations presented in the acquisition phase. During the generalization, the association transfer ability of the filling person is trialed.

[1] Rutgers Acquired Equivalence Test
[2] Functional Magnetic Resonance Imaging
[3] Electroencephalography

3 Aims

Several cognitive performance differences under RAET-like tests have been observed even nowadays among different groups, but the electrophysiological aspect of these differences remains largely unexplored.

Our goal was to determine how the complexity of visual stimuli affects cortical activity during associative learning. Specifically, we sought to identify distinguishable EEG correlates of the two tests.

The overall aim of the work reported in this thesis was to develop methods, algorithms, and software components for evaluating multichannel EEG signals recorded during associative learning tests.

The specific aims were:

- to develop an automated EEG preprocessing system, including dominant muscle activity detection.
- to investigate the applicability of machine learning for analyzing cortical activity in visual associative learning tasks with varying stimuli.
- using the listed methods, compare the RAET and the Polygon test from the view of the cortical activity.

4 Methods

4.1 Volunteers

The study adhered to the principles of the Declaration of Helsinki and received approval from the Regional Research Ethics Committee for Medical Research at the University of Szeged, Hungary (27/2020-SZTE). Participation was entirely voluntary and uncompensated. Volunteers were recruited through the authors' personal networks and were fully informed about the study's objectives and procedures. They were also assured that participation was voluntary and could be withdrawn at any time without repercussions. Those who agreed to participate signed an informed consent form.

32 individuals volunteered for the study, all of whom were deemed eligible to participate. However, due to recording errors, data from only 26 participants (14 males and 12 females) were analyzed. The average age of participants was 23.81, with a standard deviation of 5.33 years.

4.2 Study procedure

Both the RAET and Polygon tests consist of two main phases: the acquisition and test phases, each divided into multiple trials. In each trial, the participant's task was to pair an antecedent stimulus with a consequent stimulus.

The decision point in each trial is entirely self-paced, allowing participants to respond without time pressure. Once a response is made by pressing a button, feedback is displayed for one second during the learning phase. This sequence is repeated throughout the learning phase. While no feedback is provided in the test phase, the timing sequence remains unchanged.

EEG waveforms were recorded simultaneously with the RAET and Polygon tests using a 64-channel Biosemi Active Two device, sampling at 2048 Hz. This system offers a high isolation mode rejection ratio, ensuring low-amplitude common-mode interference signals. Due to this high rejection ratio and the later demonstrated algorithms, using a shielded room was unnecessary.

The electrode cap and positions were consistent across recordings, with no interruptions during the tests. The device's internal filter exhibited low-pass characteristics with a corner frequency of 410 Hz. The electrode configuration followed the standard Biosemi 64-channel layout based on the International 10-10 system.

4.3 Independent Component Analysis

One commonly used, state-of-the-art blind-source separation method is the ICA[4]; its most famous computational implementation is FastICA. As a result of the ICA, independent components are enumerated, and every channel has specific weights for these components. To reverse the ICA transformation, the components should be summarized with their weights for every channel.

4.4 Machine Learning in EEG studies

In this study, we utilize ML[5] to show that certain parts of the brain show different activity when filling out the RAET and the Polygon tests. If artificial intelligence can learn a pattern and recognize the test of a waveform, then we could state that there is a difference between them.

The following classification algorithms were used. Although we employ two types of machine learning algorithms, four distinct models are generated due to differences in feature selection. LSTM[6] and SVC[7] are applied to the raw time-domain signals of the epoch components. Additionally, two more SVC models are trained and evaluated using features derived from the Fourier spectrum of the epochs.

[4] Independent Component Analysis
[5] Machine Learning
[6] Long Short-Term Memory
[7] Support Vector Classification

Each classification was conducted using ten different train-test splits, with the test set comprising 20 percent of the available data. The accuracy distribution was analyzed per volunteer to estimate the differentiation factor of each component between the RAET and Polygon tests. If the average accuracy of any method exceeded 90 percent, the corresponding ICA component was visualized and saved.

5 Results

5.1 Two-sided reference algorithm

The developed EEG reference algorithm performed better, then the original average reference. The proposed muscle activity detector operates on the raw input data, requires referencing, and relies on the two-sided reference solution [2].

However, the need to reference was eliminated by the ICA decomposition, and the algorithm was not utilized during the evaluation of [1].

5.2 Muscle artefact marker algorithm

Analyzing the muscle artifact sections of the EEG signals using the Welch algorithm, a wide-band power increase between 350 and 650 Hz was found.

We automatically identified the muscle artifact dominant sections. Four researchers validated the method by independently confirming that the sections identified by the algorithm aligned with the areas they would have marked manually [2].

5.3 The evaluation protocol

A machine learning protocol comparing the RAET and the Polygon tests was successfully implemented and published: [1]

5.4 ML identified EEG differences between the RAET and the Polygon tests

Using the listed methods, composite plots were generated for each participant's component if any classifier strategy achieved an accuracy above 90 percent.

EEG recordings were obtained from 32 participants, each completing the RAET and Polygon tests. However, six recordings were excluded from further analysis due to issues such as data integrity, excessive noise, or an insufficient number of evaluable epochs. An additional recording was removed due to a high prevalence of artifacts. Following these exclusions, a detailed analysis was conducted on the EEG recordings from 25 participants.

The data indicates that the frontal brain region was the most responsive to the differences between RAET and Polygon. In contrast, the parietal region during the test phase exhibited the lowest level of responsiveness [1].

6 Discussion

6.1 Muscle artifact marker algorithm

It is noteworthy to detect a signal above the EEG's cut-off frequency, as this suggests that the input signals were strong enough to pass through the device's hardware filter, which attenuates frequencies above 410 Hz. This phenomenon may indicate the presence of intermodulation or overdrive effects. Additionally, when the EEG device was overloaded by a radio transmitter, such as a mobile phone, spectral power increased in the affected frequency bands, and the resulting noisy sections were removed. Another observation was that coughing by the participant had generated artifacts, which were also successfully identified and marked by the algorithm.

6.2 Two-sided common mode removal

A two-sided referencing algorithm was developed. In summary, the method involves calculating an average reference utilizing two distinct references for each instrument cable. However, since the ICA decomposition — as the core of the analysis – does not require referencing, the algorithm was not utilized.

6.3 Comparison between the RAET and the Polygon tests

To the best of our knowledge, this is the first study to utilize EEG signals and ML to differentiate between two associative equivalence learning tasks (RAET and Polygon) that vary in visual stimulus complexity and verbalizability. The results presented here enable a direct comparison of cortical activity between the original RAET and the feature-reduced Polygon.

It is well-established that the basal ganglia, besides their motor and sensorimotor functions, play a critical role in cognitive tasks and several memory processes. However, the activity of the basal ganglia cannot be directly measured with EEG; only their indirect activity reflected through connected brain networks can be observed. Functional magnetic resonance imaging (fMRI) can be employed to investigate the specific roles of deeper brain structures. By measuring changes in blood oxygenation, fMRI estimates brain activity. Numerous fMRI studies have explored cognitive tasks. and applying this approach could help determine whether the RAET and Polygon tasks engage distinct brain networks. Comparing these networks represents an important next step in this research area.

In this study, EEG signals from 24 out of 25 evaluated participants (96 percent) exhibited differences between the RAET and Polygon tests. These differences were primarily localized to the frontal region, with the most significant distinctions observed during the acquisition phase, coinciding with the decision making and the appearance of stimuli. This timing could not exclude that these differences might overlap with potential memorization processes from the previous trial.

Frontal lobe activity is associated with executive functions. attention. and working memory load. The primary distinction between the two tests lies in the complexity of the stimuli, specifically their semantic content and verbalizability. Differences in frontal cortical activity could stem from variations in attention, potentially influencing decision-making processes. These variations may arise from different learning strategies, such as explicit and implicit approaches, including concealed verbalization of the figures. Future research should survey participants' learning methods to understand these differences better.

The temporal region, known for its role in information processing, language comprehension, and memory, may also be influenced by verbalization processes, particularly in cases of verbalized learning. Post-experiment surveys should be included in future studies to account for this possible confounding factor. If verbalization during the tests influences temporal lobe activity, it would suggest that verbalization differs between the two tasks. Since these differences are most pronounced during the learning phase, they likely reflect distinct learning processes in the two scenarios.

The occipital lobe processes visual information primarily, including more complex functions such as face recognition and color determination. It also contributes to working memory. object recognition. and is functionally connected to the frontal lobe. While this area exhibited fewer differences than the frontal lobe, more significant variability was observed between the "Stimulus appearance" and "Button press" events, suggesting its involvement in specific visual and motor-related processing aspects.

By contrast, the parietal region showed minimal differences in activity between the RAET and Polygon tests. This suggests that parietal involvement is either minimal in learning and retrieval processes or relatively independent of stimulus complexity or verbalizability.

Finally, we summarize the main limitations of our ML-based results. The primary limitation of this study is its small sample size. Nevertheless, the analysis of this dataset demonstrated that artificial intelligence could detect cortical activity patterns related to stimulus complexity and verbalizability in associative learning tasks involving healthy participants. Further biomathematical analysis of the EEG data is required to pinpoint better these cortical differences, which could provide greater precision in understanding the neural mechanisms at play.

7 Summary

This thesis explores the neural mechanisms underlying associative learning using EEG[8] and advanced ML[9] techniques. Associative learning is a fundamental cognitive process in which individuals form connections between stimuli and responses. The study compares two distinct tasks – the original RAET[10] and a feature-reduced version called Polygon – to investigate how stimulus complexity affects cortical activity.

Our newly developed automatic method can mark the muscle artifacts from the EEG recordings as a competitive alternative to the existing ones.

ML classifiers, such as LSTM[11] networks and SVC[12], are used to identify differences in brain activity between the RAET and Polygon tests. The analysis focuses on distinct brain regions, including the frontal, temporal, occipital, and parietal lobes, revealing how these areas respond differently to varying levels of stimulus complexity and verbalizability.

As a result, ML found to be a reasonable method to evaluate an EEG study containing similar, but not identical trials.

Other key findings indicate that the frontal region is the most responsive to task differences, while the parietal region shows minimal variation. Although the sample size is limited, the study has demonstrated the potential of EEG and ML to uncover subtle cortical activity patterns and provides a foundation for further research into associative learning and cognitive neuroscience.

This work contributes to advancing methods for EEG signal analysis and underscores the importance of combining electrophysiological data with machine learning to better understand cognitive processes.

[8] Electroencephalography
[9] Machine Learning
[10] Rutgers Acquired Equivalence Test
[11] Long Short-Term Memory
[12] Support Vector Classification

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9 Institutional Review Board statement

The study protocol followed the tenets of the Declaration of Helsinki in all respects and was approved by the Regional Research Ethics Committee for Medical Research at the University of Szeged, Hungary (protocol number: 27/2020-SZTE).

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