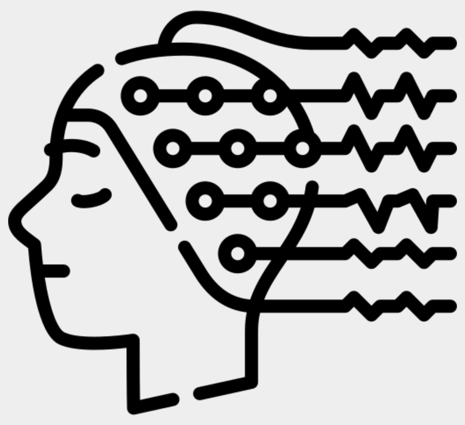


REAL-TIME SIGNAL ACQUISITION, PROCESSING AND ANALYSIS

Group members: Abdullah Doğan GÜVENER, Emre ASLAN, Yaşar CANBOLAT
Advisors: Bülent YILMAZ and Fatih ALTINDIS

INTRODUCTION

The project aims to utilize ear EEG signals for the detection of Bruxism, eye open/close state, and positive/negative emotion. Advanced signal processing techniques were applied to extract relevant features from the EEG signals and machine learning algorithms were used to classify the various states. The results demonstrate the potential of ear EEG for accurate and non-invasive monitoring of these conditions.

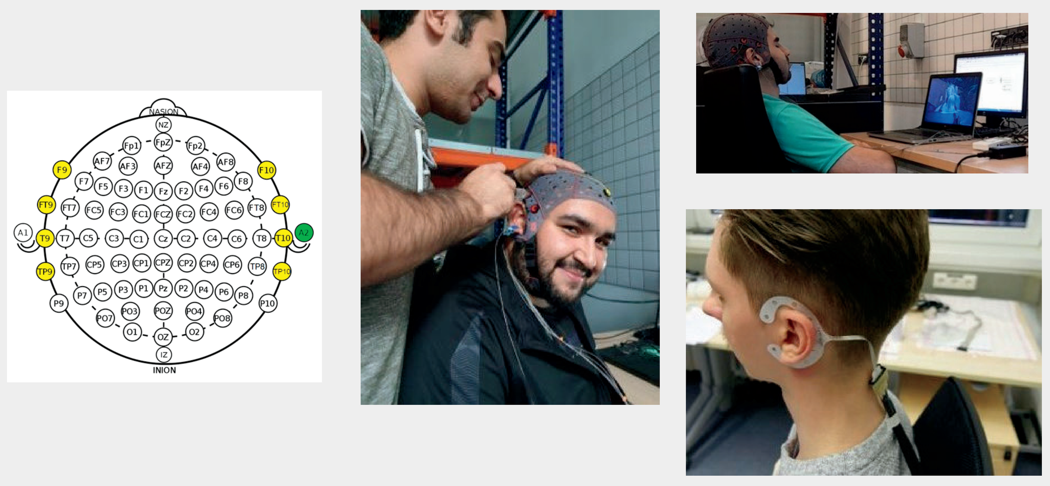
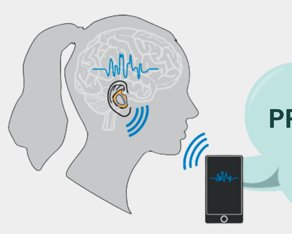


Figure 1.: Experimental setup

OBJECTIVE

- Project utilizes a combination of electroencephalography (EEG) technology and machine learning techniques.
- The processing of these signals to extract relevant information (EEG features)
- The analysis of the processed data to identify patterns
- The ultimate goal is to develop new methods for the detection and treatment of these conditions using EEG technology.

METHODOLOGY



PROBLEM DEFINITION → CROWN DEVICE → REAL TIME ANALYSIS → FEATURE EXTRACTION → ML MATLAB → PYTHON

PROBLEM DEFINITION:
- Bruxism Detection
- Eye Open Close State Detection
- Emotion Detection

CROWN DEVICE:

The Crown is an EEG device that uses signal processing to translate your brain waves into an interpretable level of focus

FEATURE EXTRACTION:
- Auto Regressive Model
- (Alfa, Beta, Gamma, Theta, Delta) Band Power
- First Difference
- Hjorth Activity, Complexity, Mobility
- Kurtosis
- Log Energy Entropy
- Skewness
- First Order Statitics

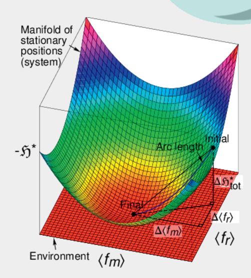
total: 30 feature for each channel

PYTHON → PREPROCESSING, ML ALGORITHMS, RIMENIAN GEOMETRY, DJANGO FRAMEWORK

PREPROCESSING:
- Artifact Reduction of EEG
  - Technical Artifacts (Power Line Interferences)
  - Biological Artifacts (Eyeblink Muscular etc.)
- Digital Filtering
  - IIR
  - FIR
  - Notch etc.

ML ALGORITHMS:
- Supervised Learning
  - Decision Trees
  - Random Forests
  - Classification
    - KNN
    - Logistic Regression
    - Naive-Bayes
    - SVM
- Unsupervised Learning
  - Clustering & Dimensionality
  - K-means
  - PCA

RIMENIAN GEOMETRY

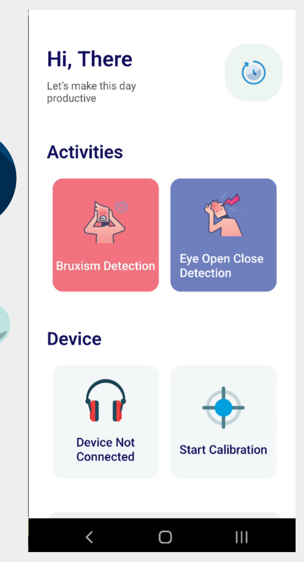


Definition: one of the non-Euclidean geometries that completely rejects the validity of Euclid's fifth postulate and modifies his second postulate.

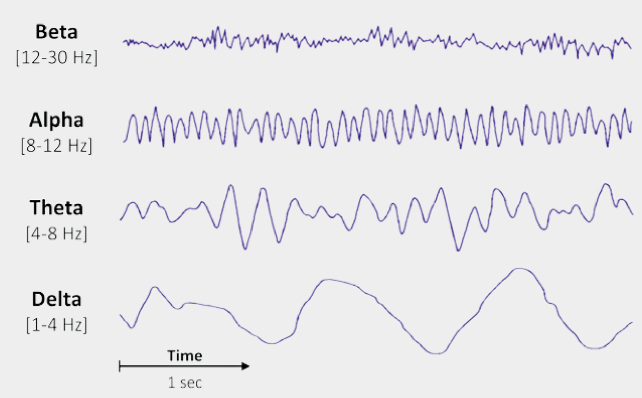
DJANGO FRAMEWORK

Surver Endpoint:
https://dashboard.heroku.com/apps/bruxismdetection

MOBILE APPLICATION



EEG signal Definition: Electroencephalography (EEG) signals are the signatures of neural activities and generally are the integrals of active potentials which elicit from the brain with different latencies and populations around each time instant. (Different frequecny composition of EEG signals)



RESULTS && DISCUSSIONS

1.1 EYE BLINK REJECTION

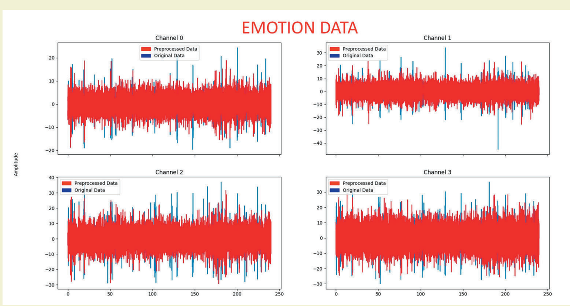


Figure 1.1 a: Eye Blink Rejection Implementation on Emotion Data

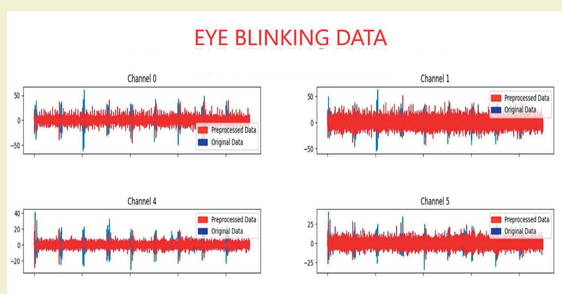


Figure 1.1 b: Eye Blink Rejection Implementation on Eye Blinking Data

- Continues wavelet transform.
- Morlet wavelet.
- Wavelet frequencies between 10.5 and 2.1 Hz.
- Determining relevant peaks by using median value of wavelet coefficients.
- Finally, excluding before and after fs/4 samples.
- 90% of the time algorithm determines right instances of the eye blinking.

1.2 BRUXISM DETECTION

Table 1.1 Bruxism Machine Learning Results with Riemannian Geometry

Machine Learning Model	Mean Accuracy value for 10-fold Cross Validation (%)
SVC: Support Vector Machine	92.03
MDM: Minimum Distance to Mean	93.36
KNN: K-Nearest Neighbors	94.08
CSP + RegLDA	92.91
CSP + TS	92.67

Figure 1.2: Bruxsism disase

- A combination of advanced signal processing techniques, Riemannian geometry-based features, and machine learning algorithms can achieve high accuracy in detecting bruxism.
- Specifically, SVC, MDM, KNN, CSP+RegLDA, and CSP+TS achieved an accuracy of 93%.
- These techniques were able to effectively extract relevant features from the EEG signals, including Riemannian geometry-based features, and classify the bruxism and non-bruxism cases.
- The high accuracy demonstrates the potential of ear EEG signals for non-invasive monitoring of Bruxism.
- The effectiveness of the used techniques, including the use of Riemannian geometry-based features, is demonstrated.

1.3 EYE OPEN CLOSE STATE DETECTION

Table 1.2 Eye Open CLose State Detection Machine Learning Results with Riemannian Geometry

EYE OPEN-CLOSE CLASSIFICATION USING RIMEANNIAN GEOMETRY

Machine Learning Model	Accuracy (%)
CSP (Common Spatial Patterns) **+ LDA** (Linear Discriminant Analysis)	80.00
CSP + TS (Tangent Space)	79.83
Cov + TS	79.61
Cov + MDM	76.77

- A combination of advanced signal processing techniques, Riemannian geometry based features, and machine learning algorithms can achieve high accuracy in detecting Eye open/close state.
- Specifically, using the combination of these techniques achieved an accuracy of 80%.
- These techniques were able to effectively extract relevant features from the EEG signals, including Riemannian geometry based features, and classify the Eye open and close states.
- The high accuracy demonstrates the potential of ear EEG signals for non-invasive monitoring of Eye open/close state.
- The effectiveness of the used techniques, including the use of Riemannian geometry based features, is demonstrated.

1.4 EMOTION DETECTION

Table 1.3 Emotion Detection Machine Learning Results with Riemannian Geometry

Classification Method	Accuracy (%)
K-Nearest Neighbors(KNN)	75.3
Random Forest	72.35
Support Vector Machine (SVM)	78.2
Logistic Regression	72.4
Naive Bayes	75.3

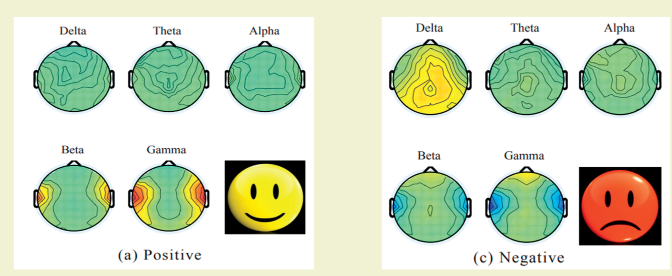


Figure 1.4 a: Positive and negative emotions

- A combination of machine learning algorithms and time and frequency domain features can achieve high accuracy in detecting emotions from EEG signals.
- Specifically, KNN, Random Forest, SVM, Logistic Regression and Naive Bayes achieved an accuracy of 78%.
- The use of multiple classifiers helped to increase the robustness of the model.
- The use of Riemannian geometry-based features highlights the importance of considering both aspects in emotion detection using EEG signals.
- This study demonstrates the potential of EEG signals for the non-invasive monitoring of emotions.
- The effectiveness of the used techniques is demonstrated.

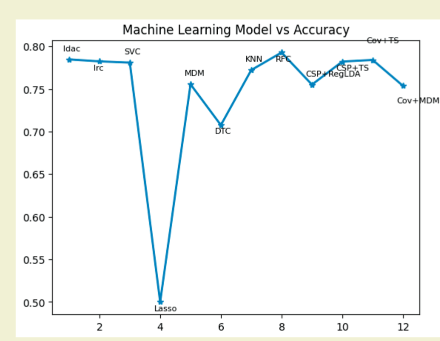


Figure 1.4 b: Classification Results by use of Rimenian Geometry

CONCLUSION

- In conclusion, the analysis of the processed data using **machine learning** algorithms, the project has identified patterns related to emotions, bruxism, and eye blinking.
- By using **rimenian** space and **artificial noise rejection tecniques** this project has been able to develop new and efficient methods for the detection and treatment of these conditions.
- It may also be considered as a pioneer work in the field of medical signal processing and machine learning.
- It can be further enhanced and improved to serve the betterment of the society.

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PROJECT PROCESS DEMO VIDEO