Brain to Joint: Joint Velocity Decoding and Visualization

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Outline

Project Goals Review

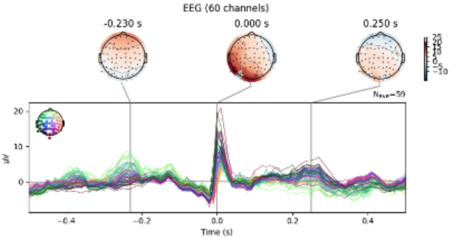
- Create a **GUI** that allows users to gain an **intuitive understanding** of some of the data **preprocessing** steps and **trade-offs** between different methods with regards to using EEG data to predict joint movements.
- This would:
  - Provide a brief roadmap to researchers and college students
  - Allow the user to gain intuition behind parameters through interactive visualization.

Review of Related Research

A Mobile Brain-Body Imaging Dataset Recorded during Treadmill Walking with a Brain-Computer Interface [1]:

- Unique comprehensive dataset
- Unscented Kalman filter
- Artifact Removal

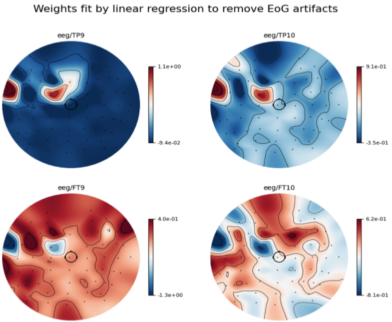
The MNE-Python to visualized the data [2]



- Pros: Good Visualization
- Cons: Requires high technical knowledge

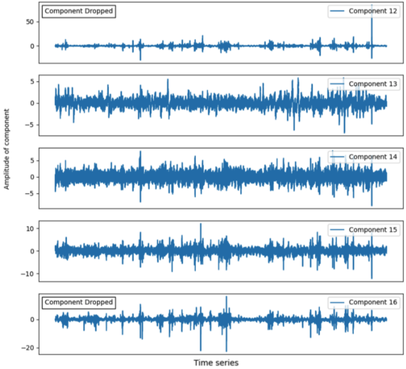
Remove Ocular Artifacts

- blah blah blah



Remove Muscle Artifacts

- blah blah blah



Bandpass Filtering

- Bandpass filtering removes other more arbitrary noise from the data after known artifacts have been removed.
- We filter the data between 0.09 and 45 Hz.

Velocity Data

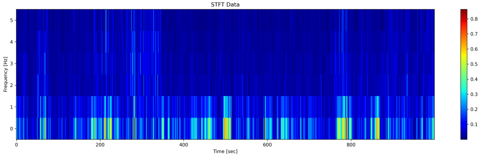
- Velocity believed to correspond more to brain signals than joint position (insert citation)

EEG Data Processing with STFT

- Short Time Fourier Transform (STFT) is used to convert the EEG data into a time-frequency domain.

$$X[k, n] = \sum_{m=0}^{N-1} x[m]w[n-m]e^{-j\frac{2\pi km}{N}}$$

  where N is the number of points in each segment, k indexes the frequency bins, and n indexes the time steps.
- This allows us to see how the frequency of the brain signals change over time windows to map to the joint velocity.



LSTM

- Long Short-Term Memory (LSTM) is a type of recurrent neural network that is capable of learning long-term dependencies. It **selectively retains** or **forgets** information over time.

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

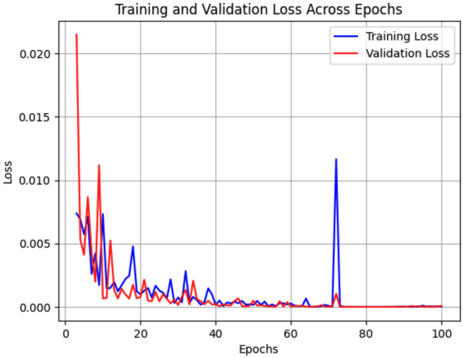
  - c_t: New cell state at time t.
  - f_t: Output of the forget gate, decides which parts of the previous cell state c_{t-1} to retain or forget.
  - c_{t-1}: Previous cell state.
  - i_t: Output of the input gate, controls how much of the new candidate cell state to add to the cell state.
  - $\tilde{c}_t$: New candidate cell state, generated by processing the current input.

LSTM (Visualization)

a visualization of the LSTM result

Transformer

- The Transformer model is a type of neural network architecture that is designed to learn **complex long time dependencies** the data efficiently.



Interface Development

- The GUI will allow users to interact with the data and see the results of the preprocessing and prediction steps.
- The GUI is built using the `PyQt5` library.

GUI Demo

there should be a video here or a live demo or screenshots

Key Insights and Achievements

- Biological data

Next Steps

- steps

References

[1] He, Yongtian, et al. “A Mobile Brain-Body Imaging Dataset Recorded during Treadmill Walking with a Brain-Computer Interface.” Scientific Data, vol. 5, no. 1, 24 Apr. 2018, https://doi.org/10.1038/sdata.2018.74. Accessed 2 Apr. 2020.

[2] Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A. Engemann, Daniel Strohmeier, Christian Brodbeck, Roman Goj, Mainak Jas, Teon Brooks, Lauri Parkkonen, and Matti S. Hämäläinen. MEG and EEG data analysis with MNE-Python. Frontiers in Neuroscience, 7(267):1–13, 2013. doi:10.3389/fnins.2013.00267.