Neurophysiological Working Memory Task Classification from Magnetoencephalography using Deep Learning

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Introduction

Many advances in neuroscience have been driven by deterministic signal and image processing algorithms. However, as our understanding of complex neural networks in the human brain increases, machine learning approaches have recently become indispensable for progress.
Mesoscale modeling of the unique subject specific neural activation patterns describing higher cognitive functions, such as working memory, traditionally requires computationally expensive algorithms. Thus, parallelized implementation of high dimensional modeling methodologies based on machine learning may support extraction of neurophysiological network interaction patterns, even in near-real time.
In this experiment, we trained a Deep Learning model to classify neural oscillatory patterns associated with different working memory demands. Training was accelerated using DIGITS and four NVIDIA GTX Titan GPUs.

Aims

- Present multichannel neurophysiological signals obtained from magnetoencephalography to a Deep Learning system by extracting and encoding relevant features into image sequences.
- Employ convolutional neural networks to train classifiers that detect oscillatory patterns of neural activity in sensor space over the prefrontal cortical area that differentiates between working memory tasks.

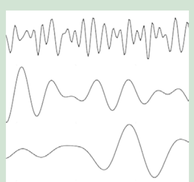
Experimantal Design

Conditions

- Working memory (WM) tasks are classified using two "N-back" face recognition sequences [1]:
- 0-back: Users remember one face for low-load
- 2-back: Users compare current face to second preceding face for high-load

Frequency

- Simultaneous β/γ decrease and θ increase scale with WM load [1]
- α & θ modulate memory encoding [2]



Anatomy

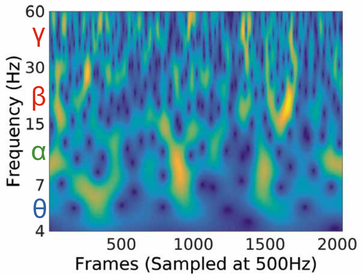
- Unique activation during recognition task with memory load in Left Anterior Prefrontal Cortex (Brodmann Area 10) [3]

Magnetoencephalography (MEG) Preprocessing

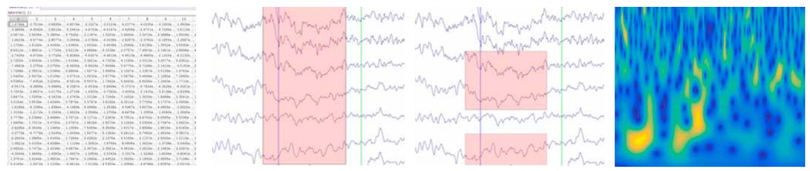
- MEG Data is collected from the Human Connectome Project (HCP): 500-Subjects + MEG2 Data Release [4].
- Minimal task-MEG channel-level preprocessing scripts are run as outlined in HCP documentation [5]:
  1. DataCheck – Perform sanity checks on MEG data
  2. BadData – Clean bad segments and channels throughout scans
  3. ICAclass – Correct signal artifacts using Independent Component Analysis (ICA) decomposition
  4. tMEGpreproc – Segment continuous signals and organize trial information, including categorical tags and response accuracy

Frequency Analysis

- A wavelet of log-normal shape as defined in the frequency domain is employed to create a scalogram that clearly represents fast changes in the frequency bands of interest
- The wavelet is transformed for Y-values and convolved over the signal for X-values



Producing Images for Training

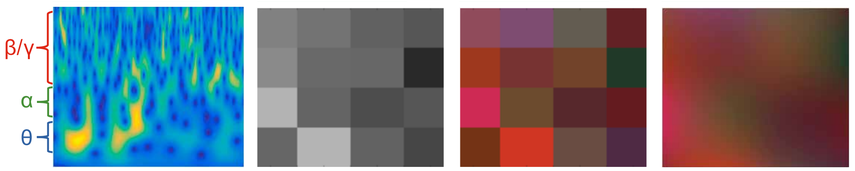


Step 1 – Import preprocessed MEG data into MATLAB

Step 2 – Parse data for trials with correct responses, then sort by condition

Step 3 – Parse trials for channels within relevant sensor space

Step 4 – Conduct wavelet transform across each channel



Step 5 – Gather β/γ, α & θ spectral power per frame

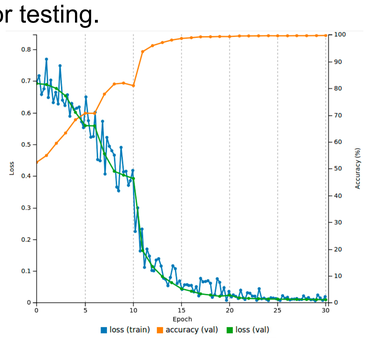
Step 6 – Normalize values at each sample into intensities in a sensor space grid

Step 7 – Combine band intensities into lossless RGB PNG images

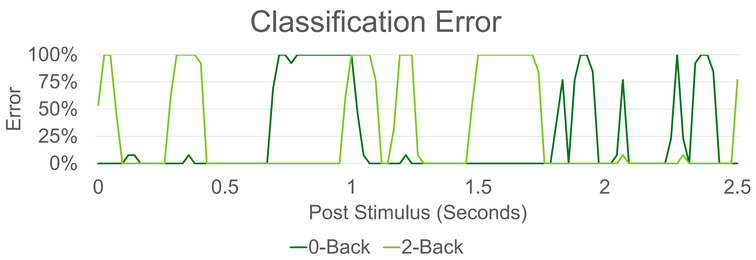
Step 8 – Use 2-D gridded, cubic interpolation to expand to 49px by 49px

DIGITS Training

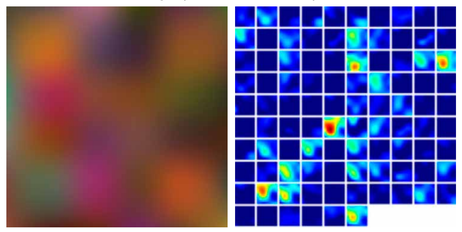
- For each subject, all frames from 0-back and 2-back categories are sorted into respective folders – two trials from each condition are saved in a separate folder to conduct classification error analysis.
- Approximately 33,000 PNG images per user are indexed by condition and shuffled in a text file to create a DIGITS dataset – 50% of all images are allocated for validation and 25% for testing.
- An image classification model is trained using AlexNet [6] – DIGITS training, shown in the graph at right, which lasts approximately 3 minutes.
- The model is used to classify frames from classification error analysis trials. Results are unshuffled to recreate temporal representation of categorical trial segments and accuracy is represented in binary.



Results



- We used mean condition accuracy for simple trial-wise evaluation across N=1286 frames. These frames correspond to a 500 Hz sampling rate across 2.5 seconds after stimulus. In accordance with the figure above, a mean below 0.5 indicates an accurate, overall trial classification. Upon testing sample 0-back and 2-back trials not presented to the model during training, classifiers produced sufficient means for accurate classification at 0.236±0.425 and 0.278±0.448 respectively (mean ± SD).
- We are in the early stages of exploring what patterns the network is learning. Displayed at right are a single input frame and network activations from the first convolutional layer of a trained model.



Conclusion

This implementation shows that MEG data from a localized brain region can be presented to a deep learning system in order to classify and differentiate between neurophysiological tasks.
From here, we intend to expand the model to include further spatial and temporal information. We will use accompanying MRI-based brain morphology to train on whole-brain source space, rather than focusing only on localized sensor space. Furthermore, we will expand temporal representation beyond static frequency features using a Long-Short Term Memory (LSTM) recursive network model that can capture dynamically changing patterns in oscillatory fluctuation.

References & Acknowledgements

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