EEG Analysis of Motor Execution vs. Imagery: Neural Patterns and Dynamics

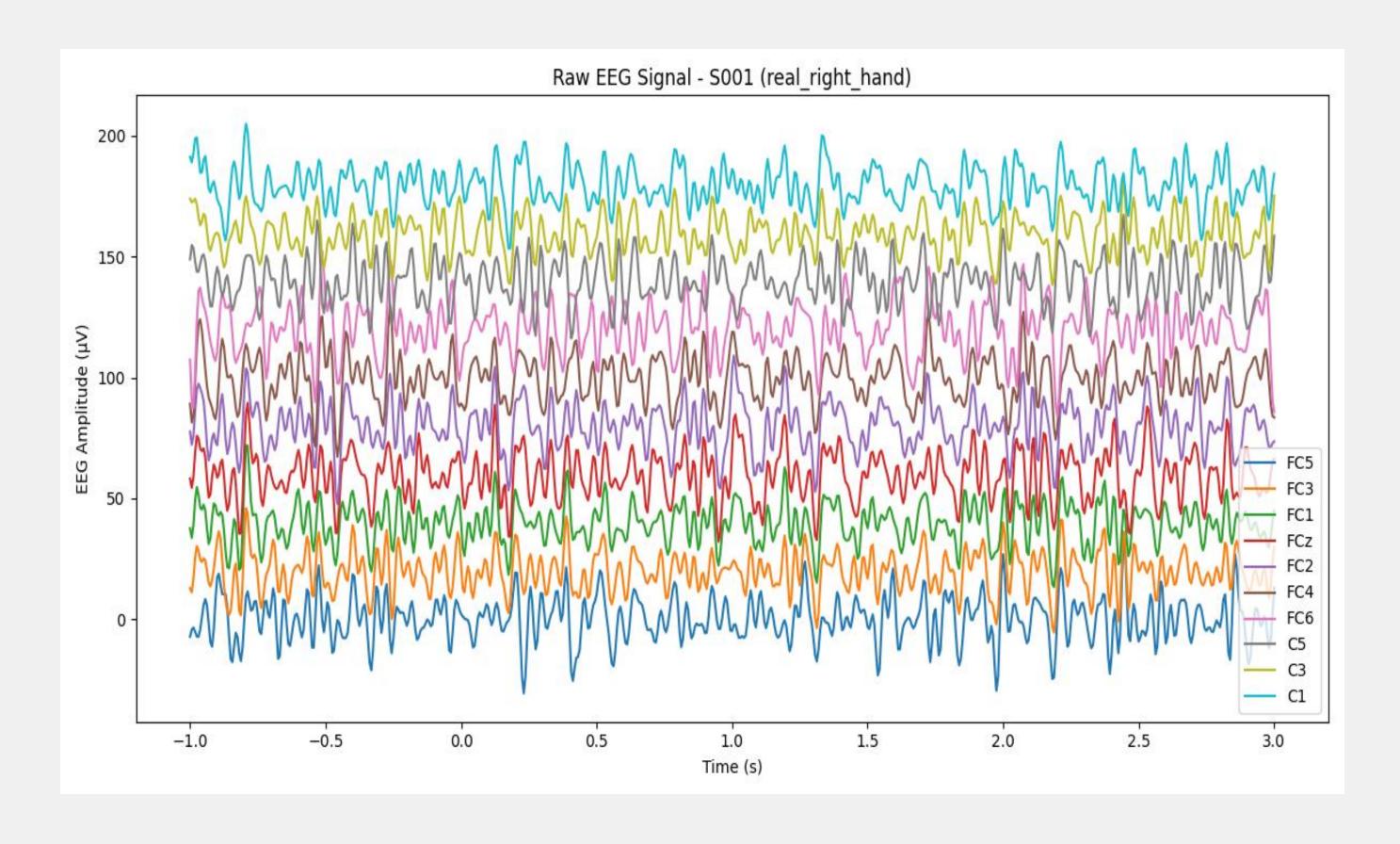
Flavio Caroli

Introduction

- How similar are the neural patterns of real movement and imagined movement?
- Using the PhysioNet EEG Motor Movement/Imagery Dataset
- Prior research suggests they are similar
- Applying multiple techniques to verify this

Data Analysis and Preprocessing

Raw EEG Signal



Preprocessing Pipeline

- Bandpass Filtering (6-30 Hz)
- ICA (Automatic or Manual)
- Extract and Concatenate the Epochs

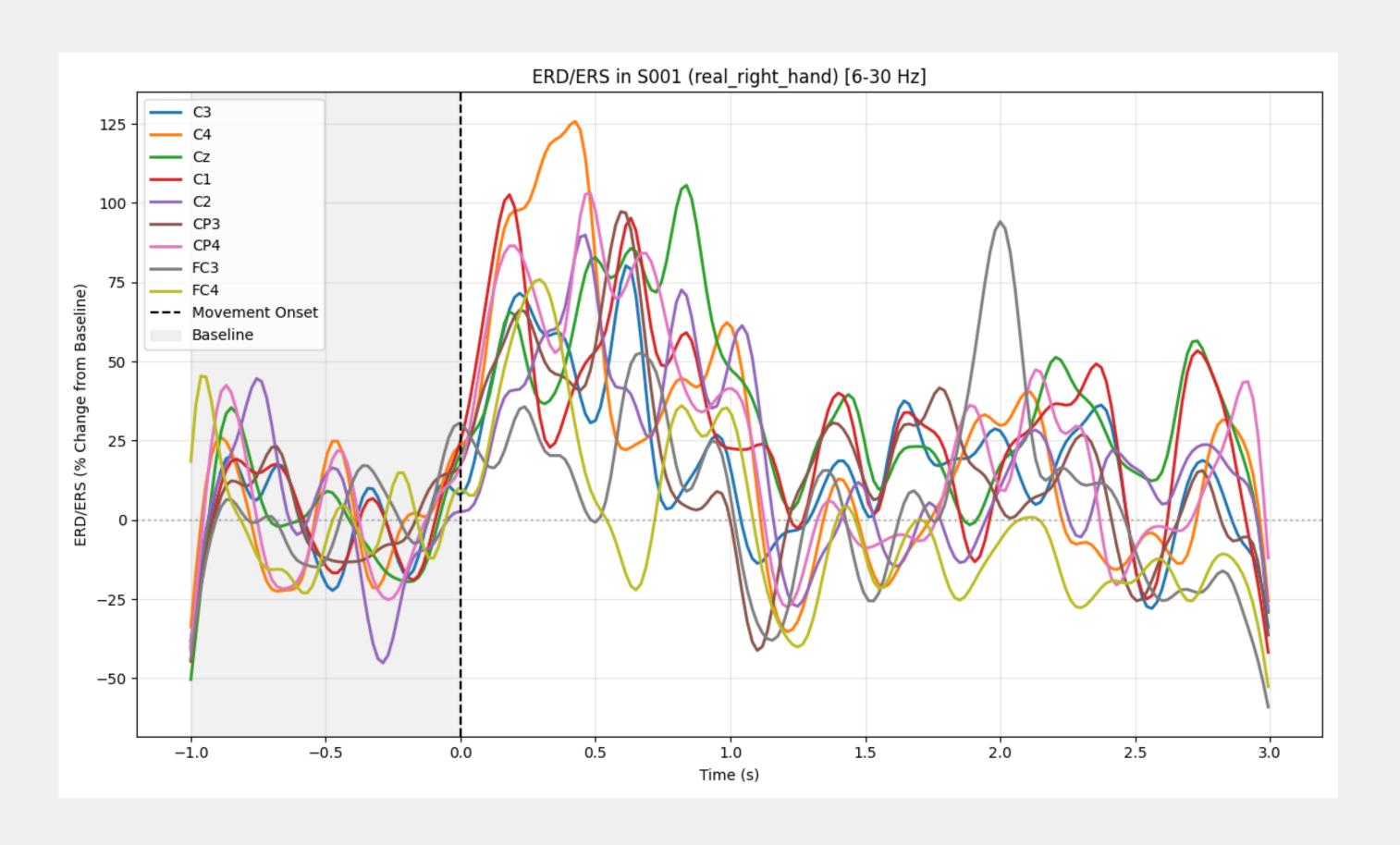
```
ef process_eeg_automatic(subjects, data_path, apply_ica=False, bandpass=(6, 30),
  # Define selected runs for each condition
  selected runs = {
      "real_right_hand": [3, 7, 11],
      "imagined_right_hand": [4, 8, 12]
  for subject in subjects:
     data_dict[subject] = {"real_right_hand": [], "imagined_right_hand": [], "rest": []}
     for condition, run_numbers in selected_runs.items():
         for run number in run numbers:
              run = f"R{str(run_number).zfill(2)}"
              edf_file = os.path.join(data_path, subject, f"{subject}{run}.edf")
             try:
                 # Load raw data
                 raw = mne.io.read_raw_edf(edf_file, preload=True)
                 # Standardize channel names and set montage
                 mne.datasets.eegbci.standardize(raw)
                  montage = mne.channels.make_standard_montage("standard_1005")
                 raw.set_montage(montage)
                 raw.set_eeg_reference("average", projection=True)
                 raw.filter(bandpass[0], bandpass[1], fir_design="firwin")
                 # Apply ICA for artifact removal if requested
                 if apply_ica:
                     raw clean = apply ica(raw, n ica components, subject, run)
                     raw_clean = raw
                 # Extract epochs for Right Hand and Rest conditions
                  events, event_id = mne.events from_annotations(raw_clean)
                  if len(events) == 0:
                     print(f" ▲ No events found for {subject} - {run}, skipping...")
                     continue
                  # Extract "Right Hand" epochs (T2)
                 if "T2" in event id:
                     epochs = mne.Epochs(
                         raw_clean, events, event_id={"Right Hand": event_id["T2"]},
                         tmin=tmin, tmax=tmax, baseline=(None, 0), preload=True
                     data_dict[subject][condition].append(epochs["Right Hand"])
                     print(f" ☑ Extracted {len(epochs['Right Hand'])} epochs for {subject} - {run} ({condition})")
```

ICA Artifacts

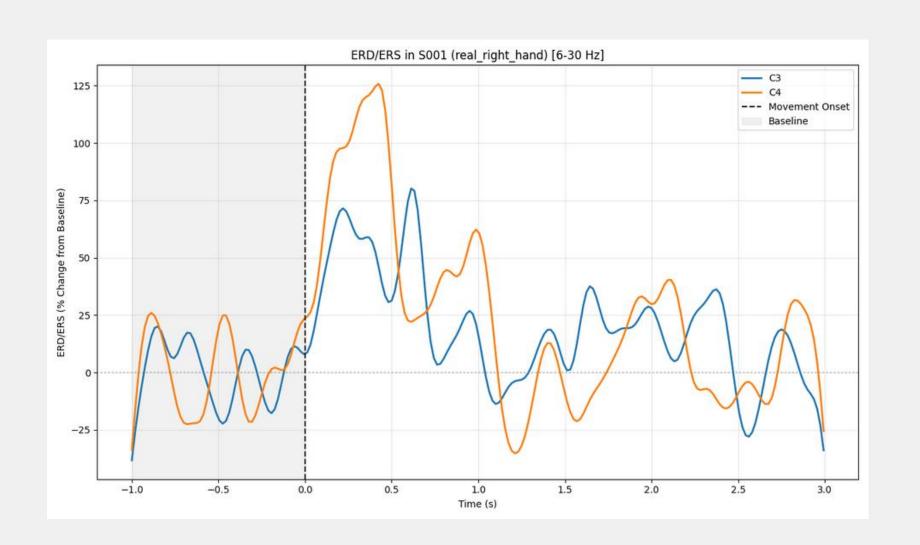
- Find bad EOG
- Find bad ECG
- Find Muscle Artifacts

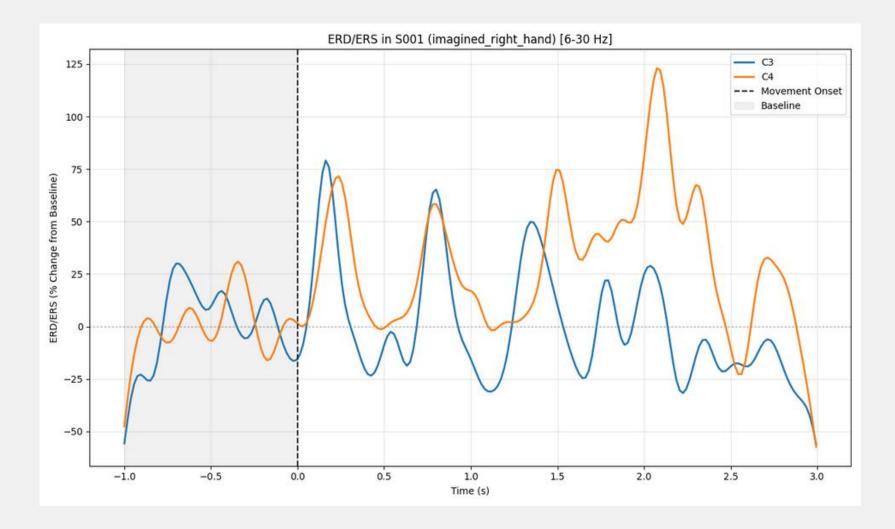
```
def _fit_ica(raw, n_components, subject, run):
    """Helper function to fit ICA and detect artifacts"""
   ica = ICA(n_components=n_components, random_state=42, method="fastica", max_iter=500)
   ica.fit(raw)
   # EOG artifact detection
   eog_indices = []
   frontal_channels = [ch for ch in raw.ch_names
                      if ch.lower().startswith(('fp', 'f'))
                      and not ch.lower().startswith(('fc', 'ft'))][:2]
   if frontal_channels:
       eog_indices, _ = ica.find_bads_eog(raw, ch_name=frontal_channels)
   eog_indices = eog_indices[:2] if len(eog_indices) > 2 else eog_indices
   # ECG artifact detection using kurtosis
   ica_sources = ica.get_sources(raw).get_data()
   kurtosis_values = stats.kurtosis(ica_sources, axis=1)
   # Z-score kurtosis values
   kurt_z = (kurtosis_values - np.median(kurtosis_values)) / (
       np.median(np.abs(kurtosis_values - np.median(kurtosis_values))) + 1e-6
   ecg_indices = np.where(kurt_z > 2.5)[0].tolist()[:2]
   # Muscle artifact detection
   muscle_indices, _ = ica.find_bads_muscle(raw, threshold=0.5, 1_freq=7, h_freq=45)
   # Combine artifacts
   all_artifact_indices = list(set(eog_indices + ecg_indices + muscle_indices))
   ica.exclude = all_artifact_indices
   print(f"  Detected {len(ica.exclude)} artifact components: {ica.exclude}")
   return ica
```

Event-Related Des/Synchronization



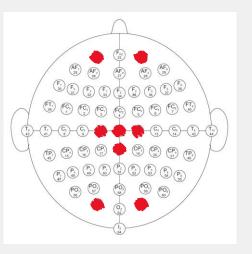
ERD/ERS in Real and Imagined Movement

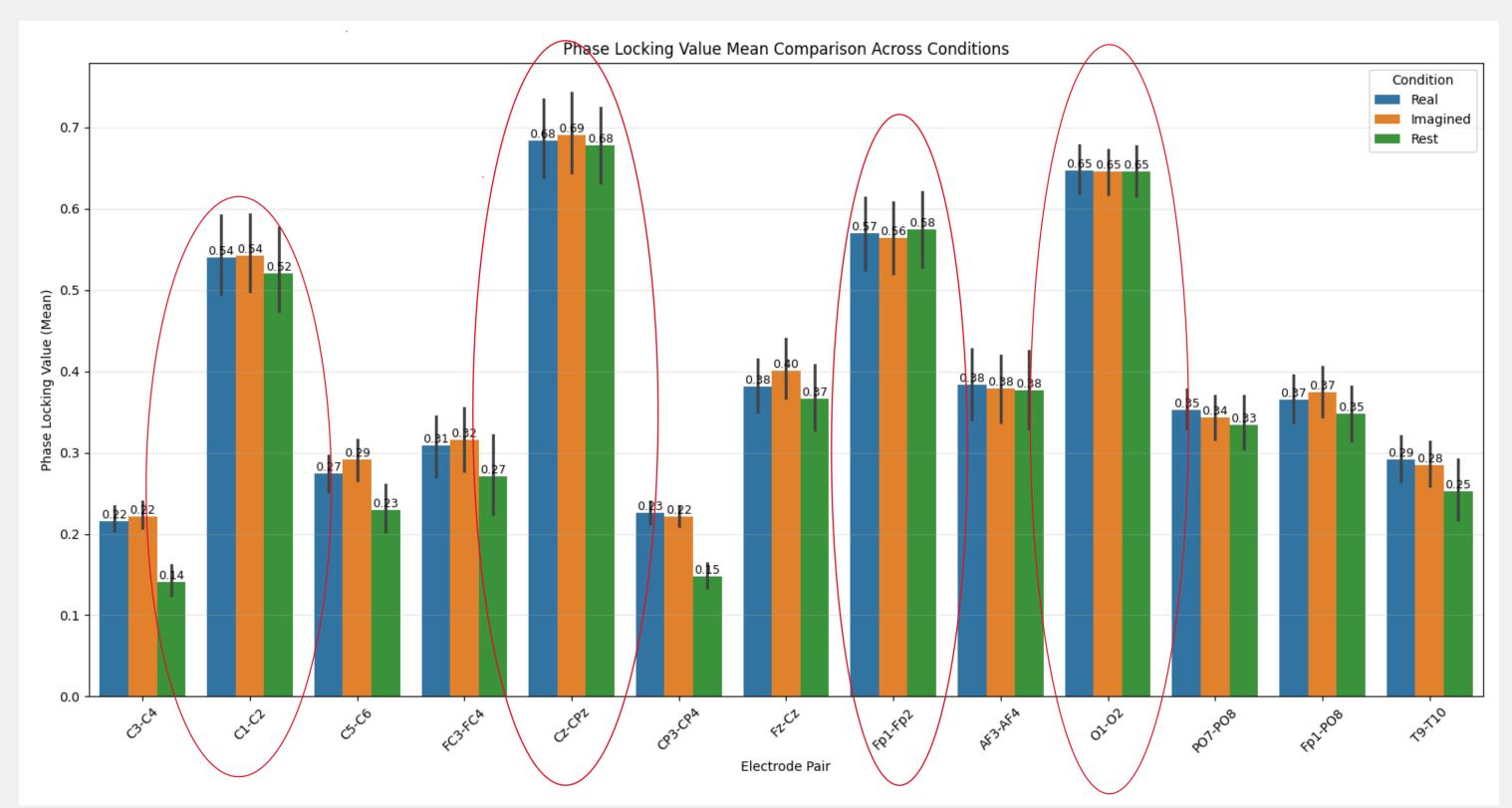




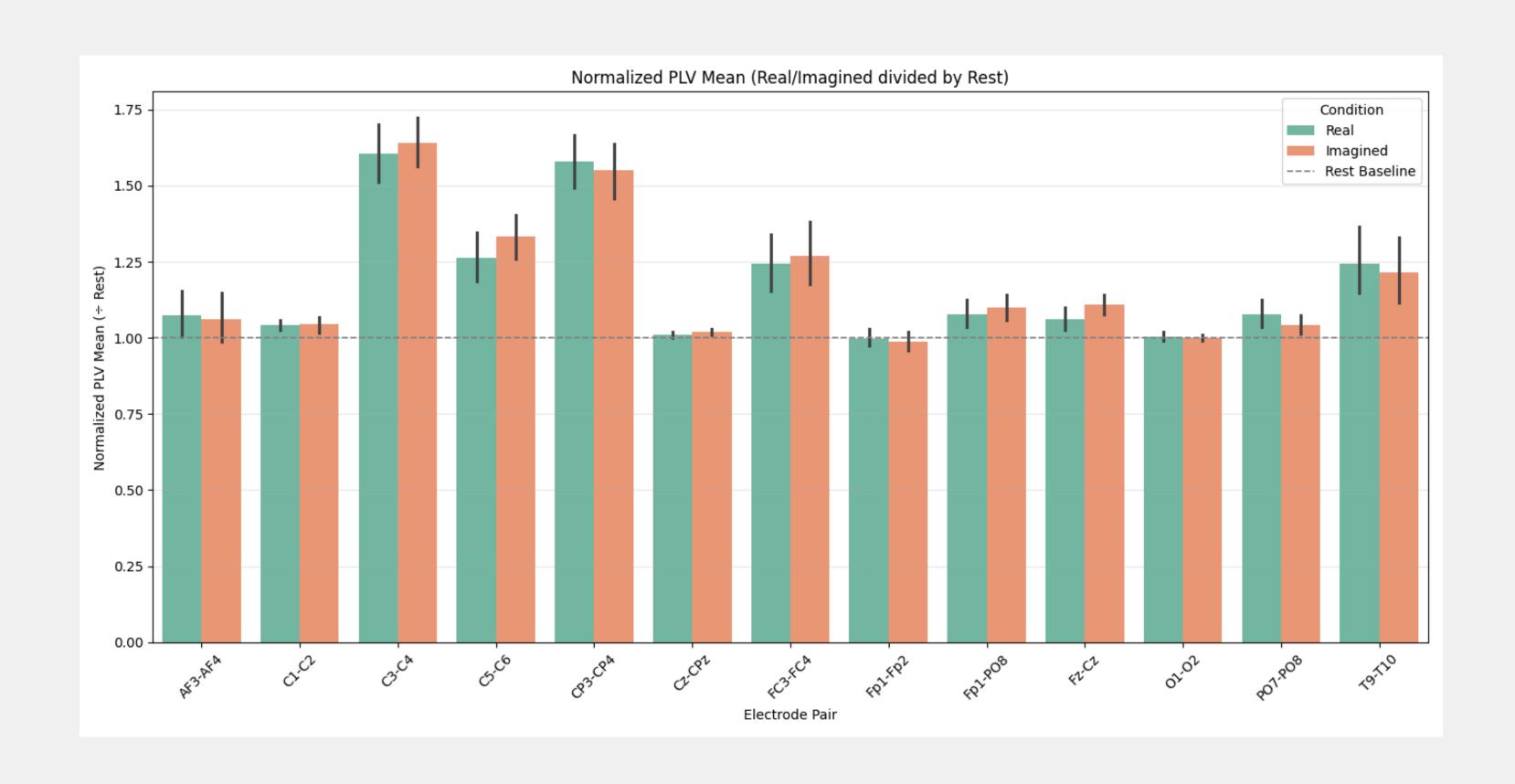
Connectivity Metrics

PLV Mean

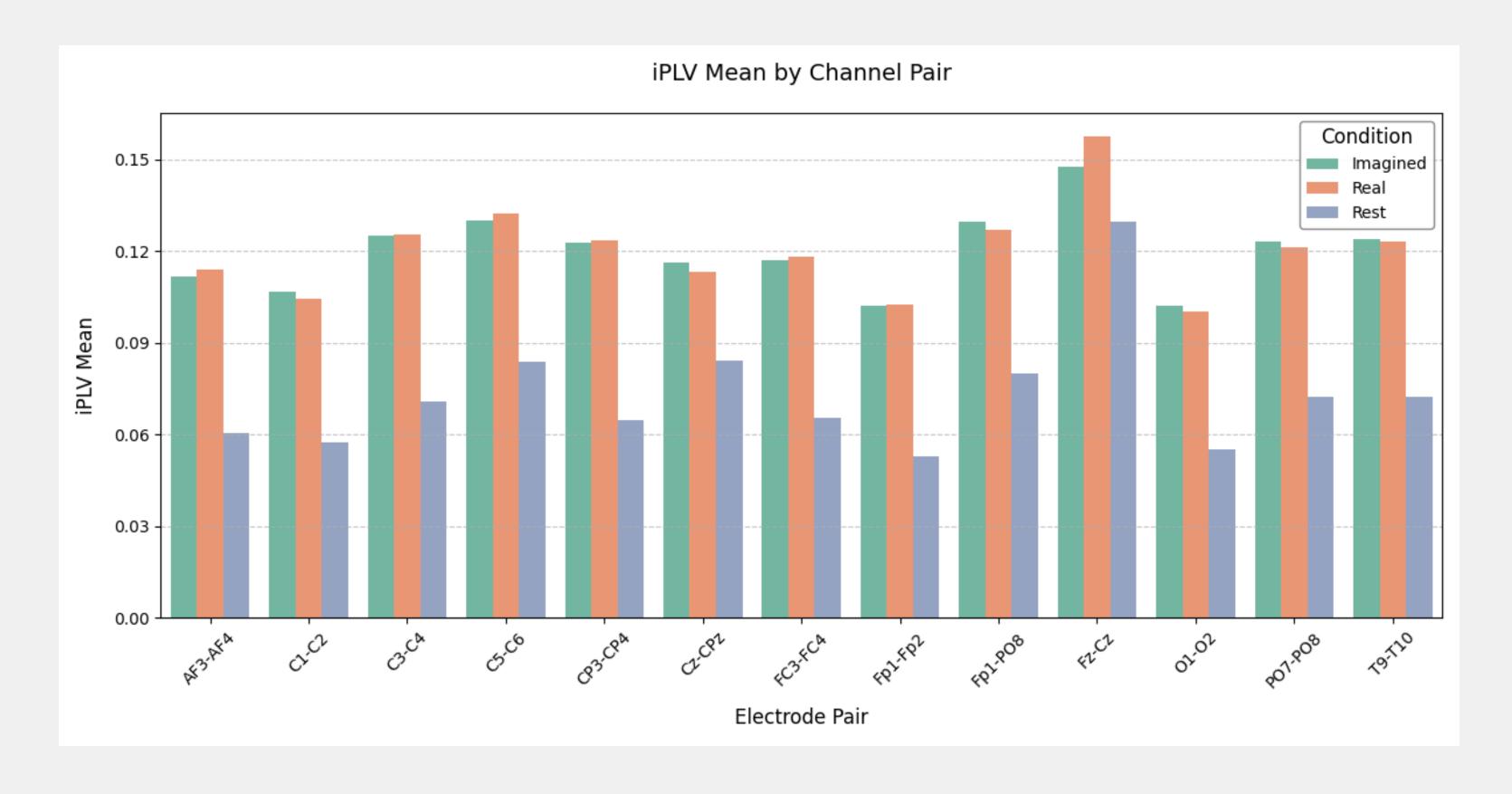


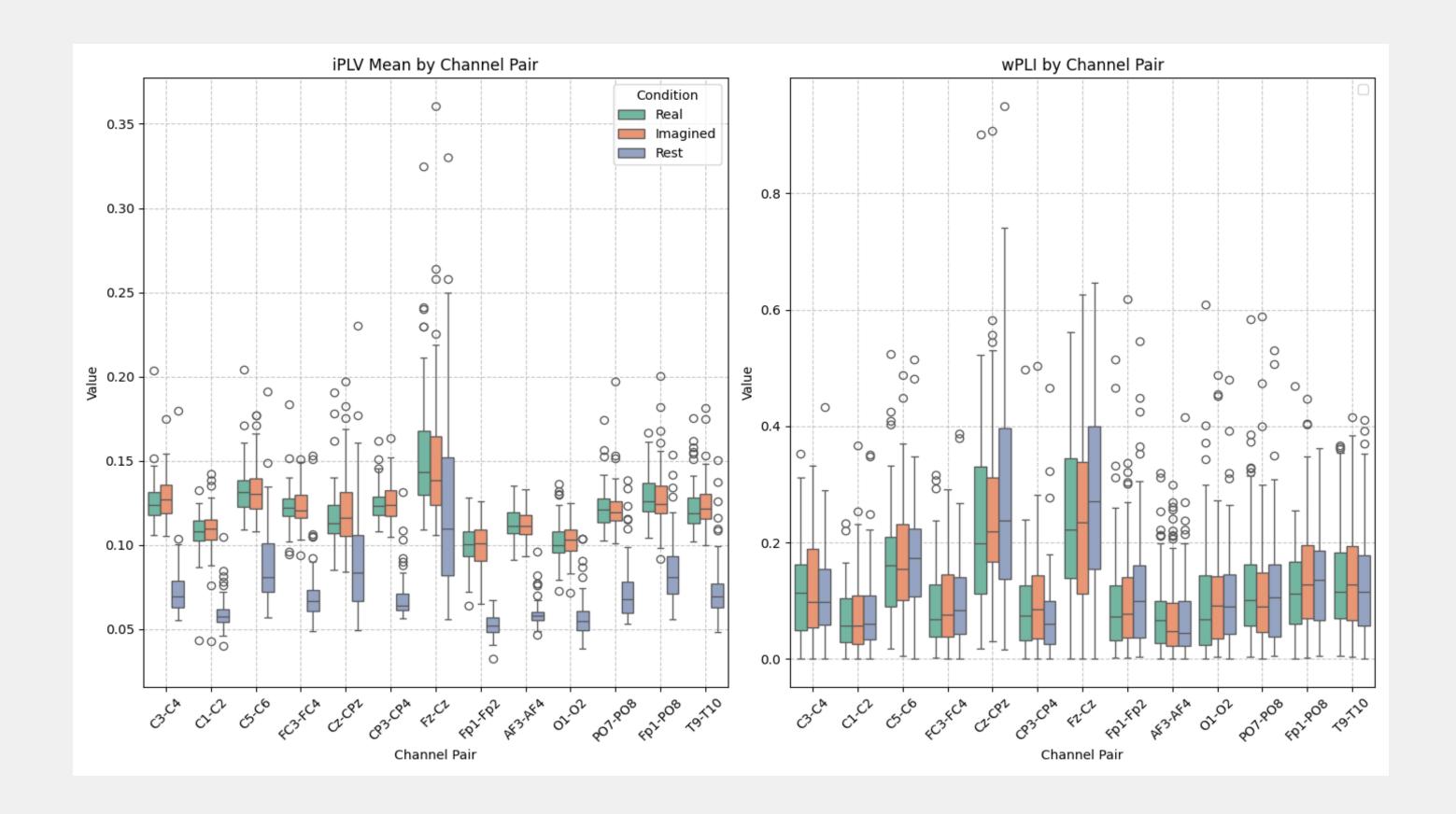


Normalized PLV Mean

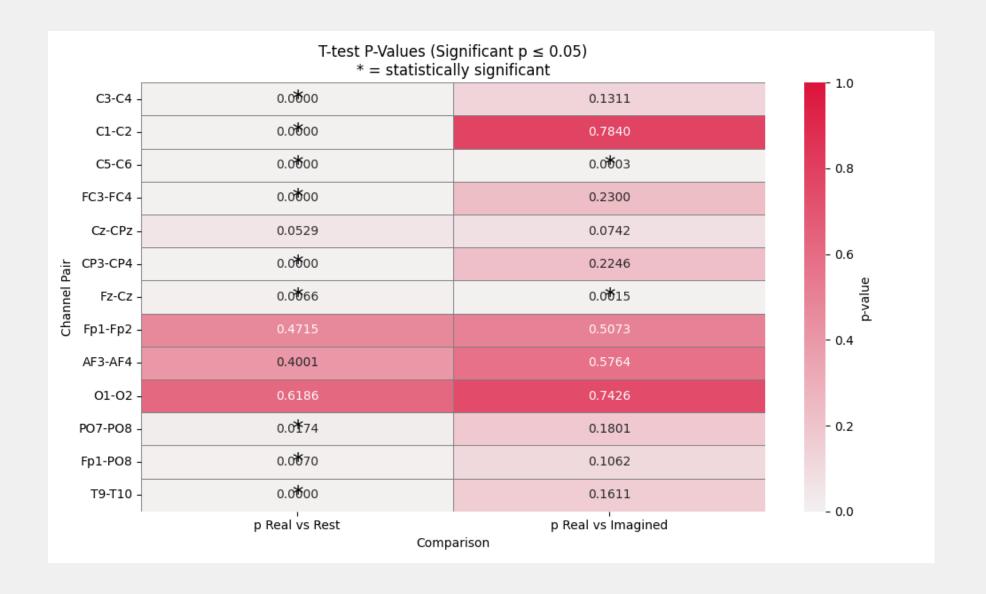


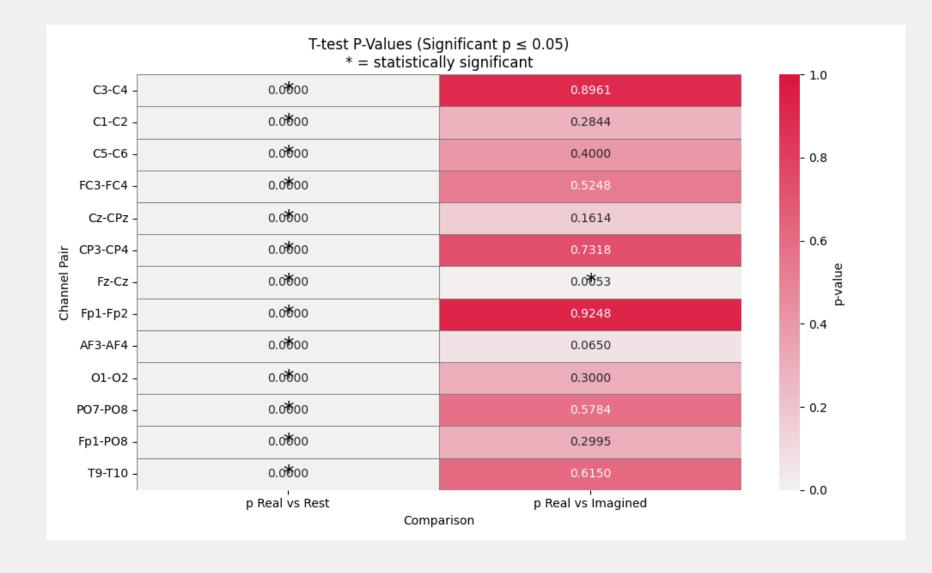
iPLV Mean



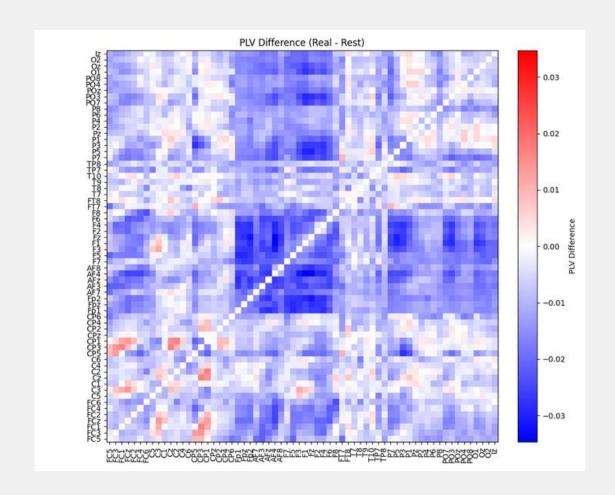


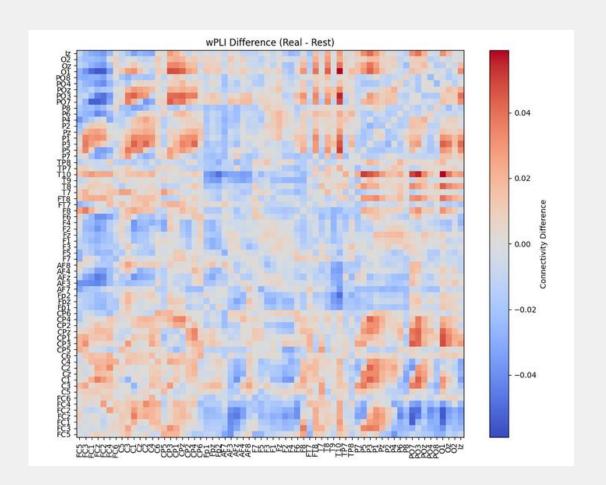
T-Test for PLV and iPLV

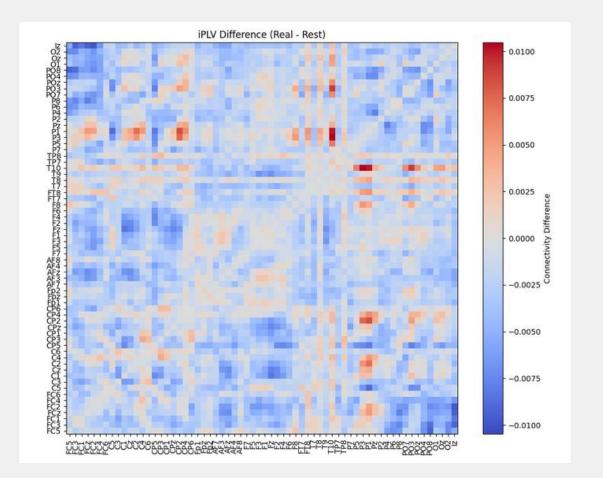




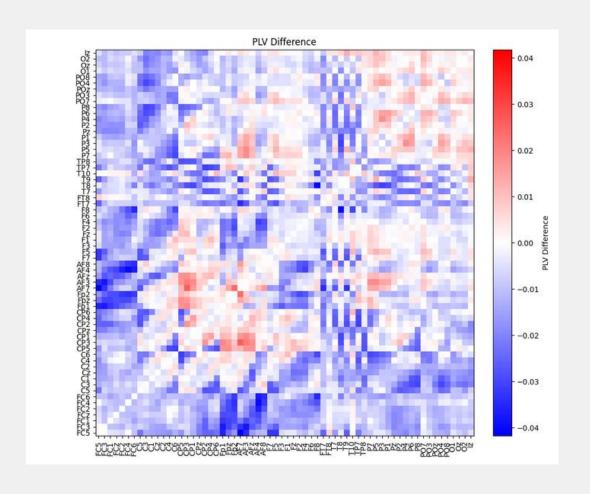
Matrix differences for Real vs Rest

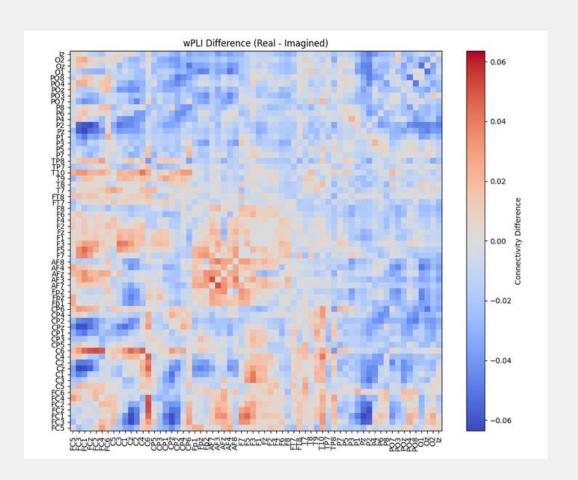


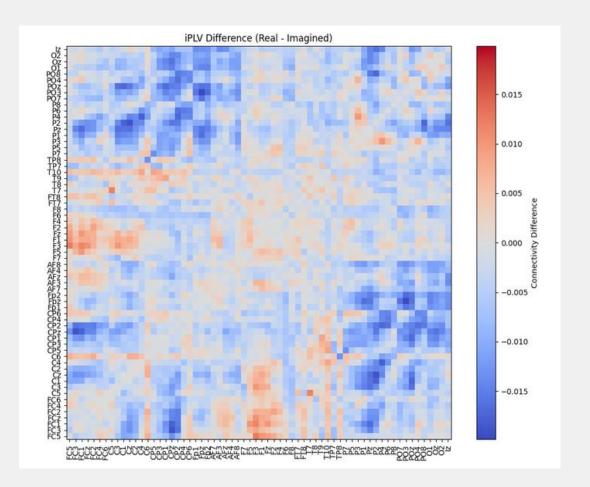




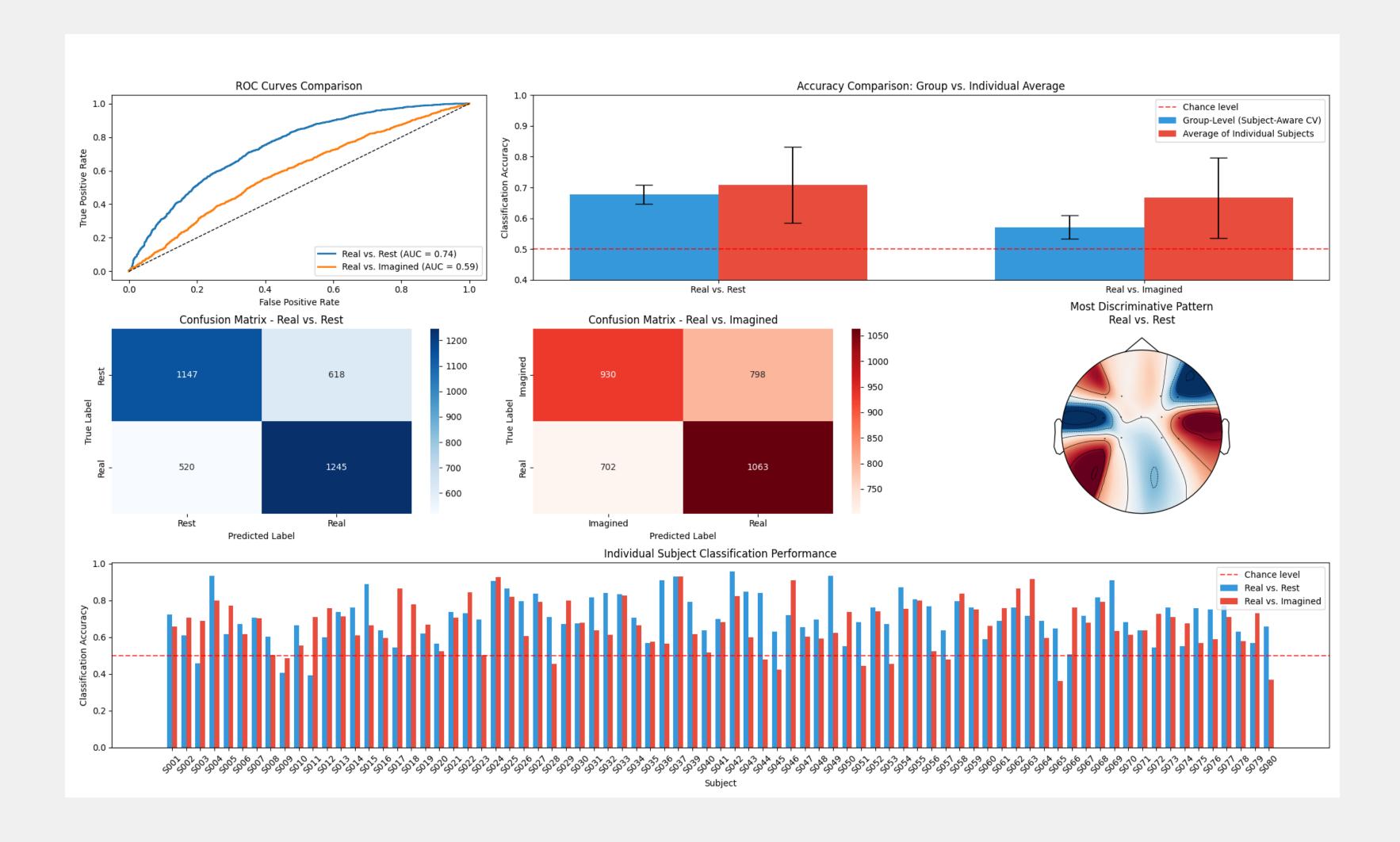
Matrix differences for Real vs Imagined

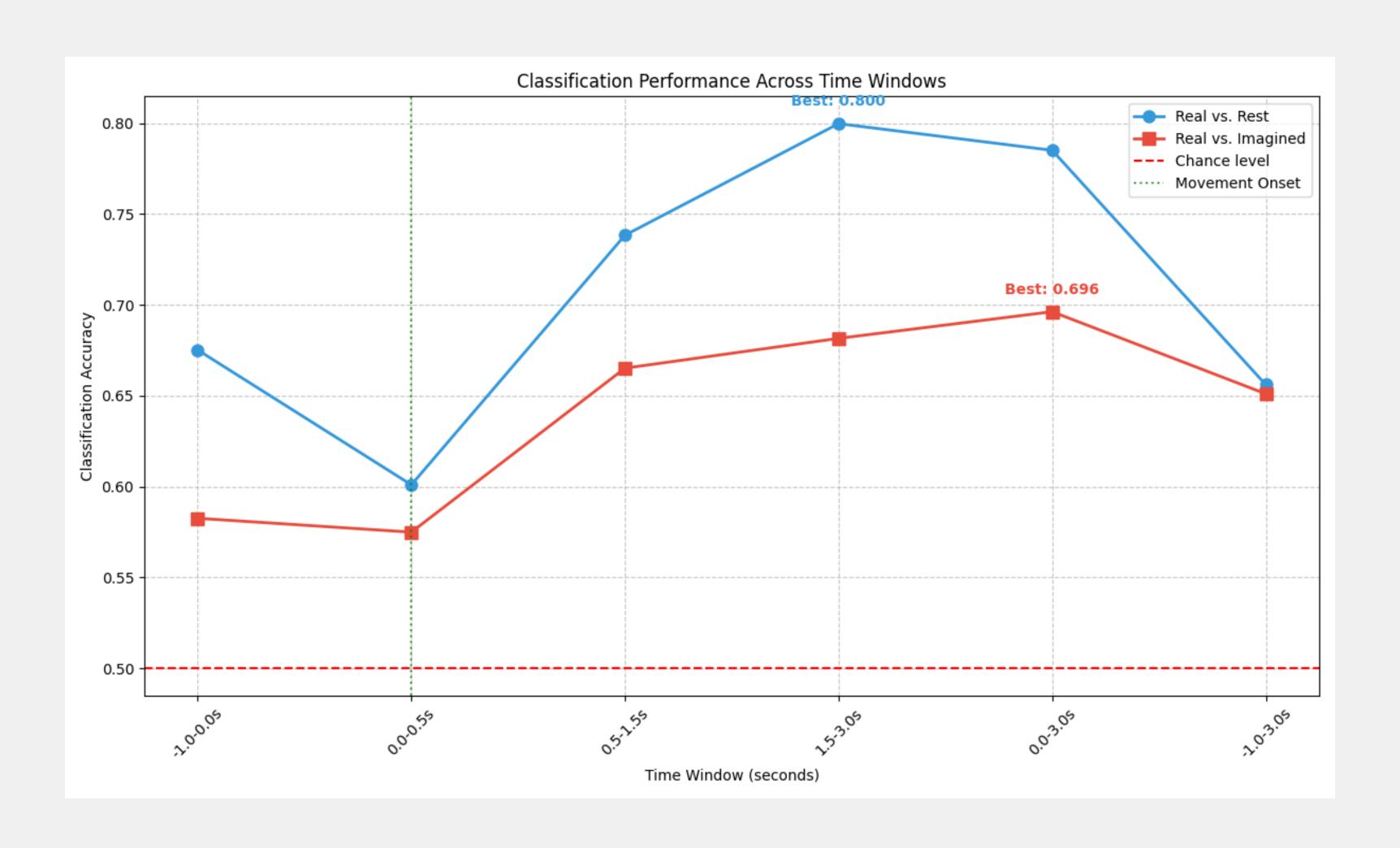


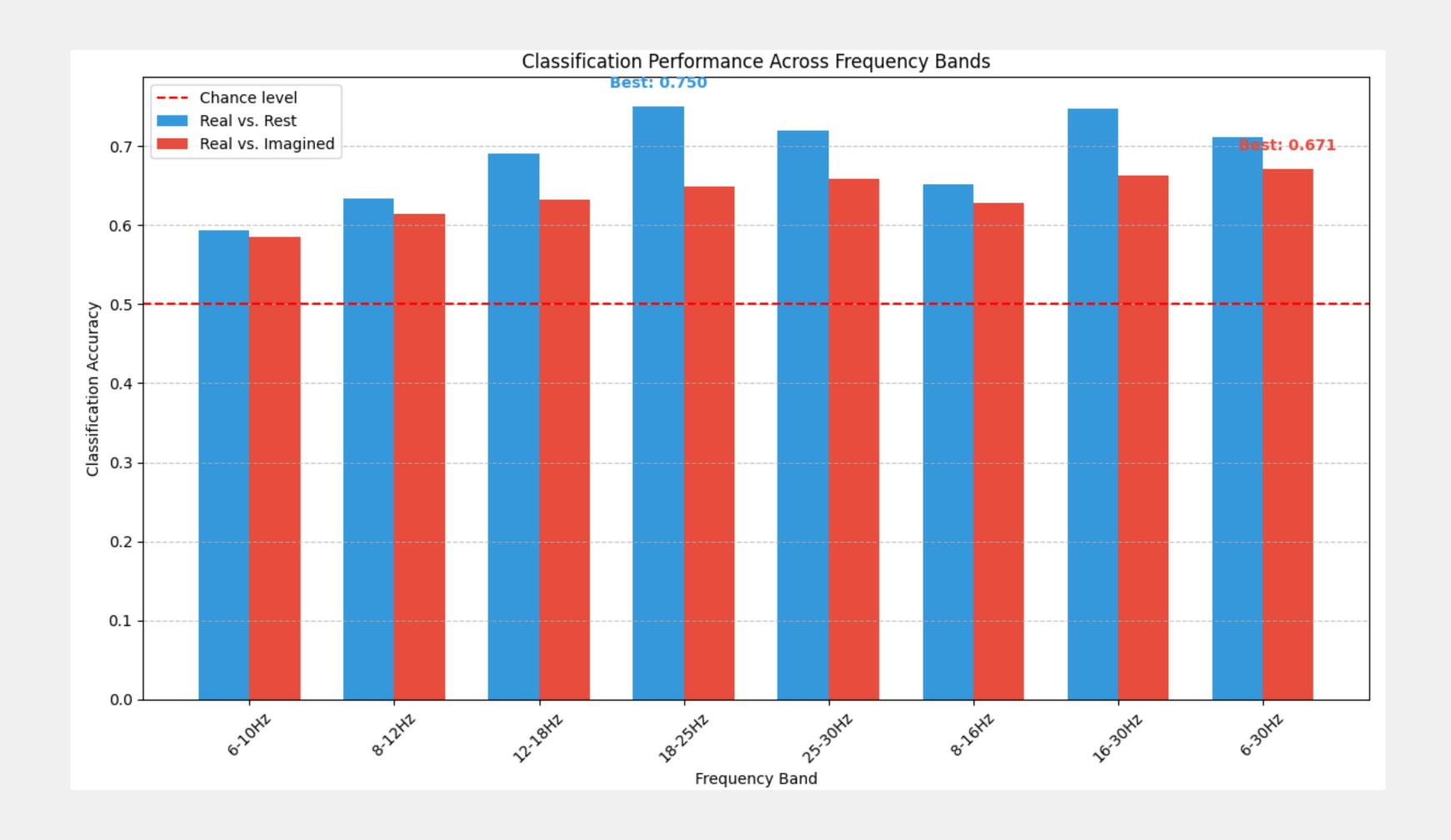




Classification

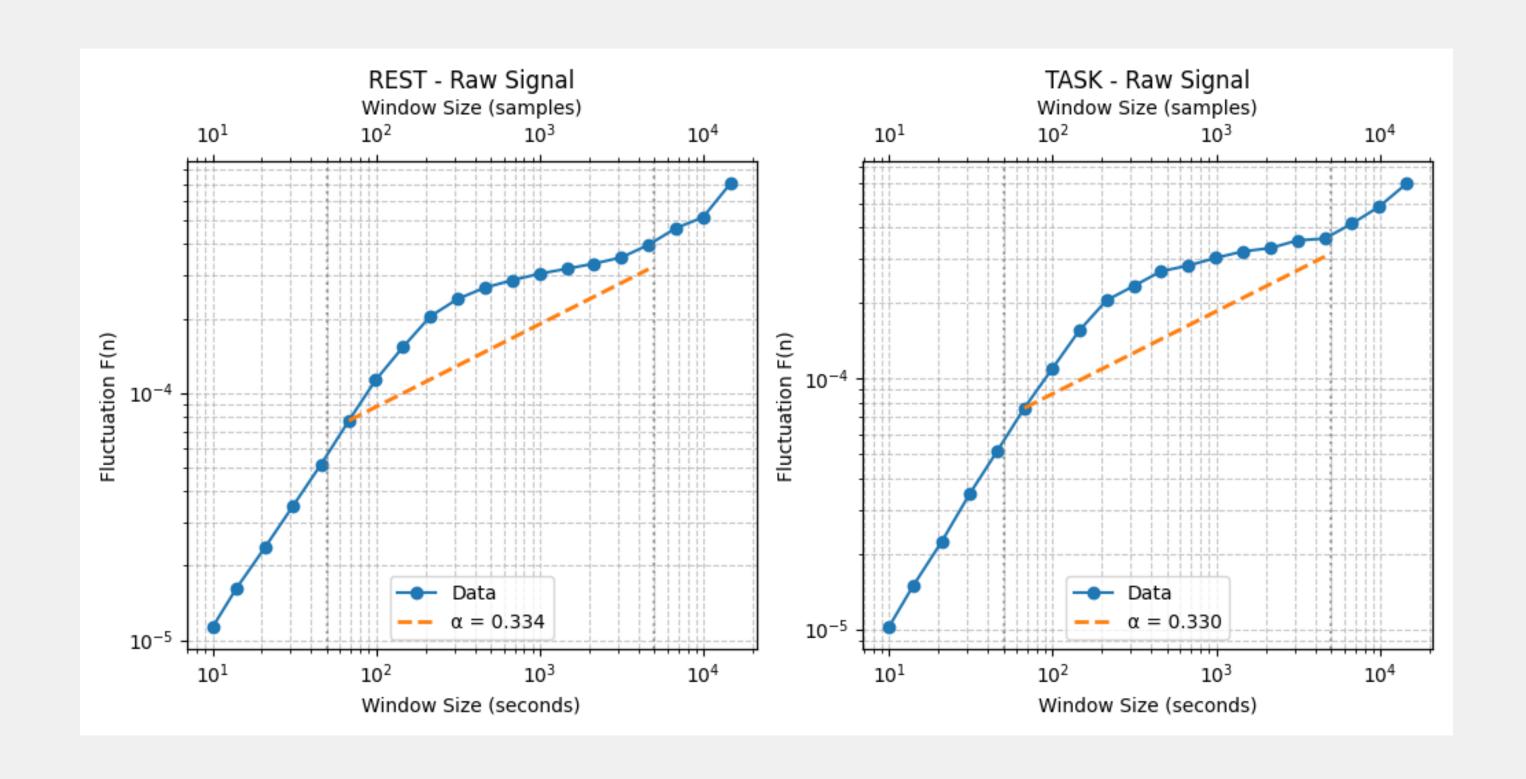




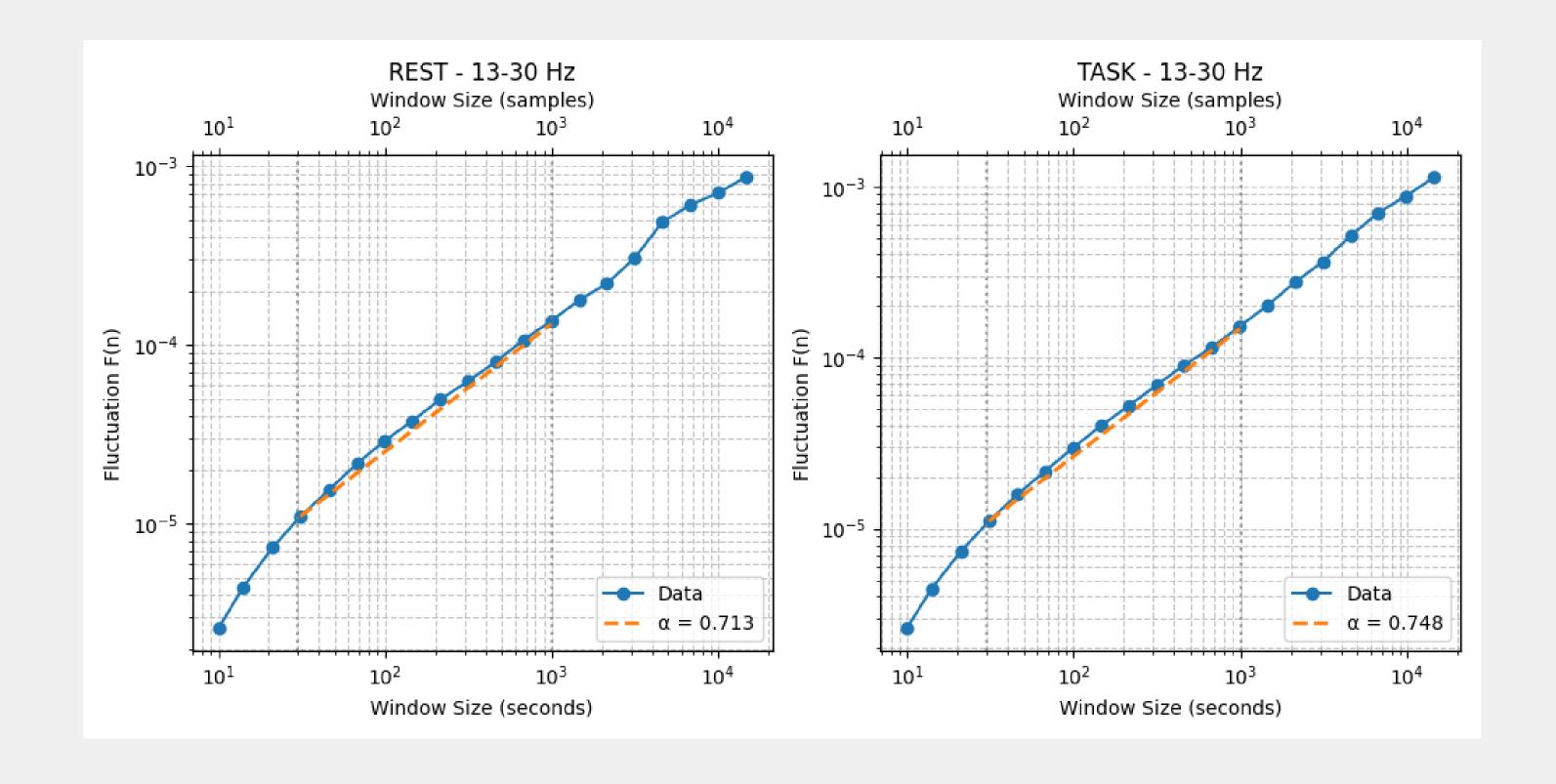


DFA Metric

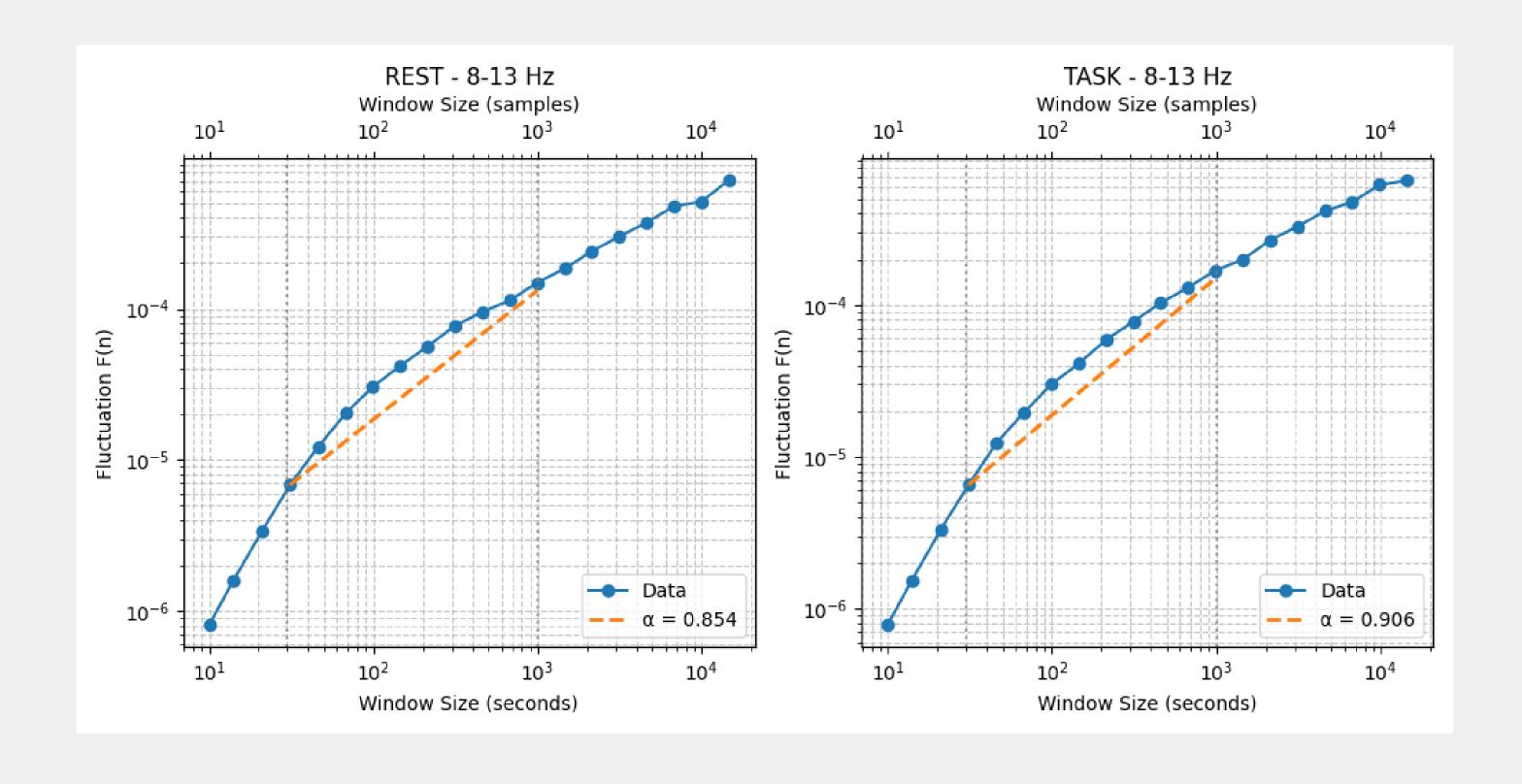
DFA Applied on Raw Signal

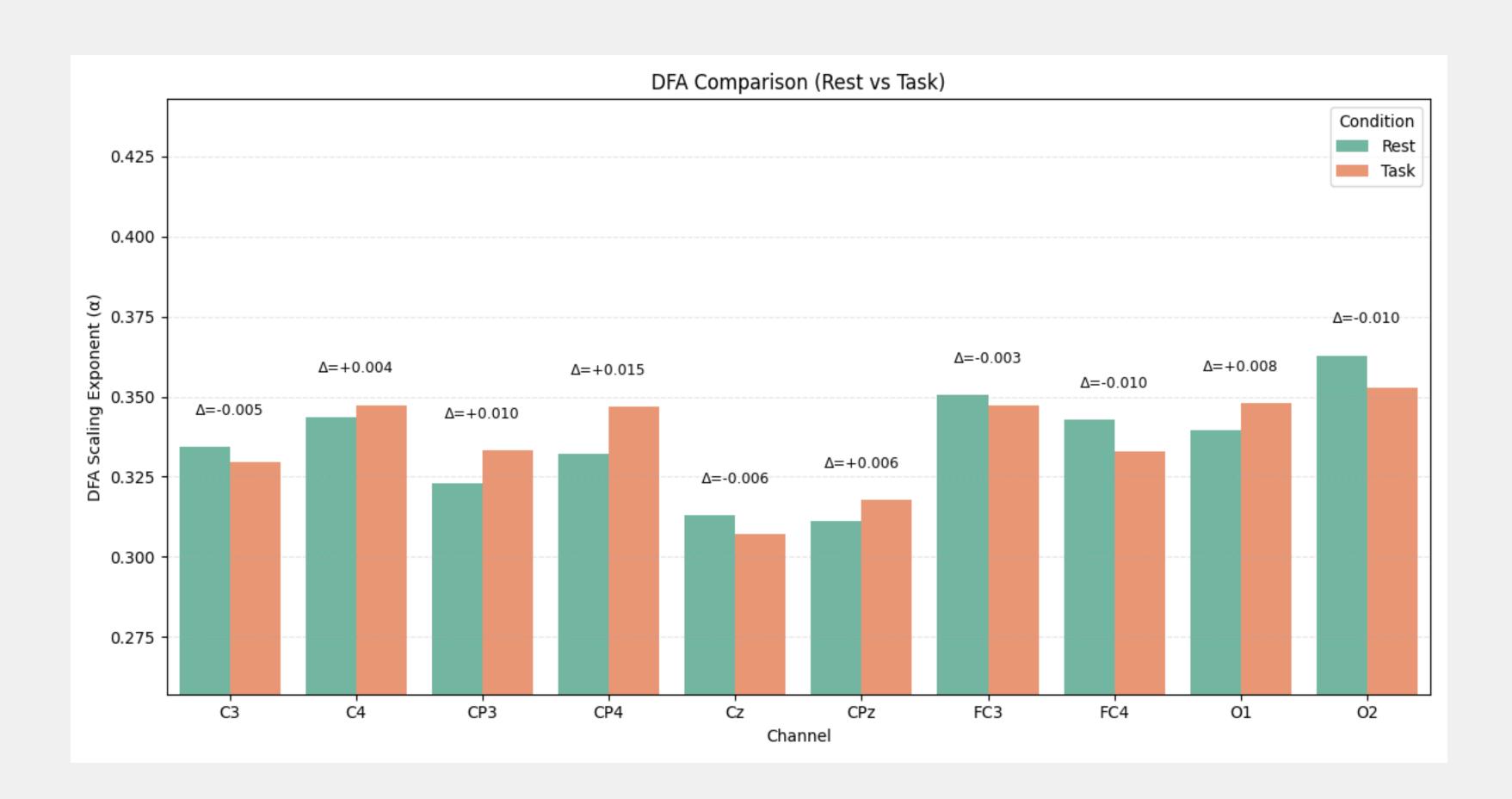


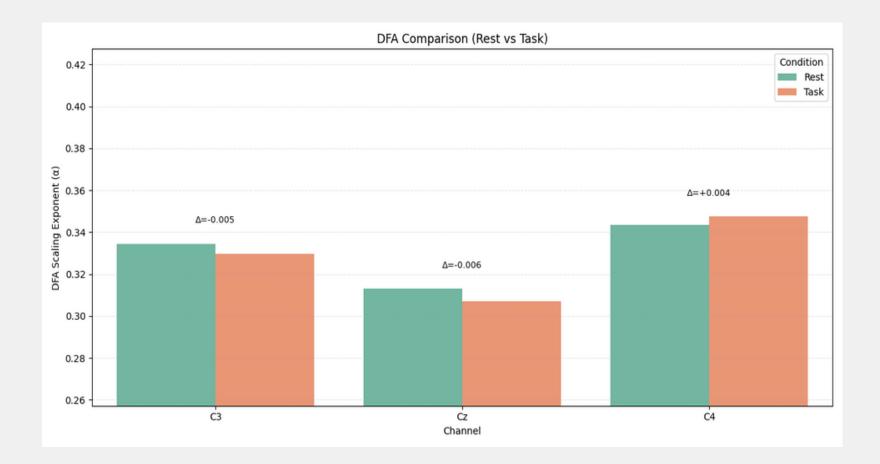
DFA Applied on B Band

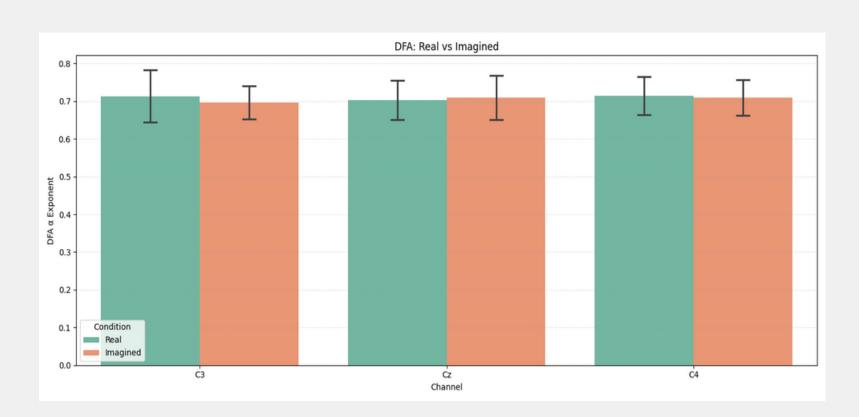


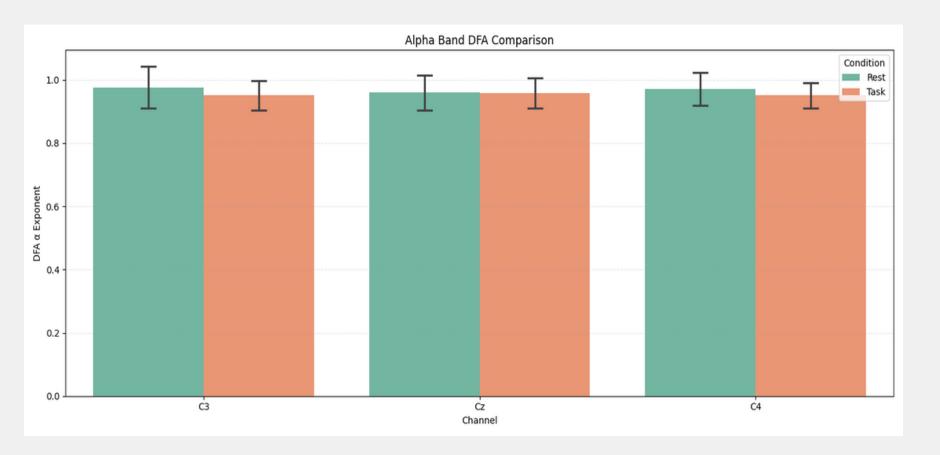
DFA Applied on α Band

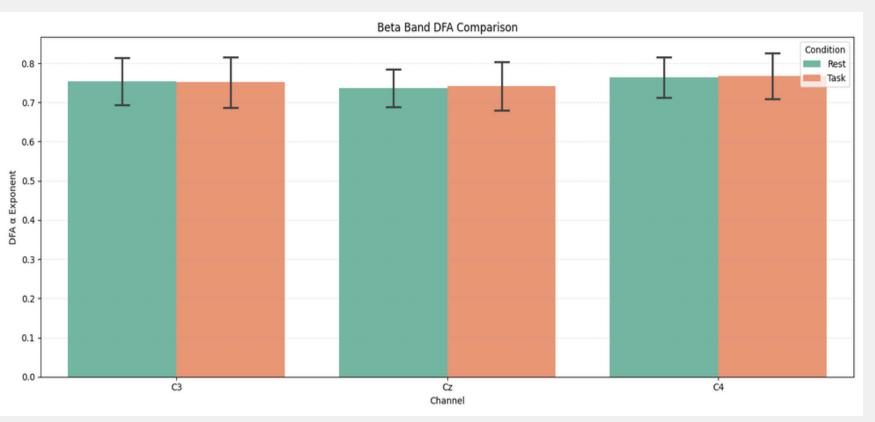












Conclusion (Real vs Imagined movement)

- They have similar activation
- They have similar activation patterns
- They have similar DFA values

"The latter outcome is not tragic, as failure is what scientists experience every day in the lab. Resilience to failure, humiliation, and rejection are the most important ingredients of a scientific career."

- György Buzsáki, in The Brain from Inside Out

References

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