Mental Fatigue Prediction from Multi-Channel ECoG Signal

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ICASSP 2020

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- Neural Biomarkers of Fatigue
- Feature Selection and Classification
- Conclusions

Introduction: Traumatic Brain Injury (TBI)

- Life-long cognitive deficits
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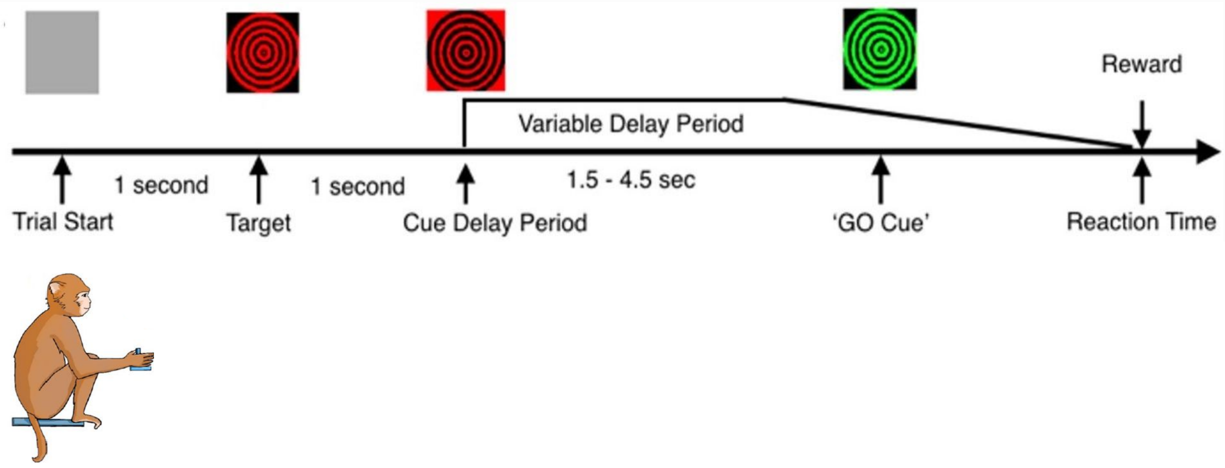
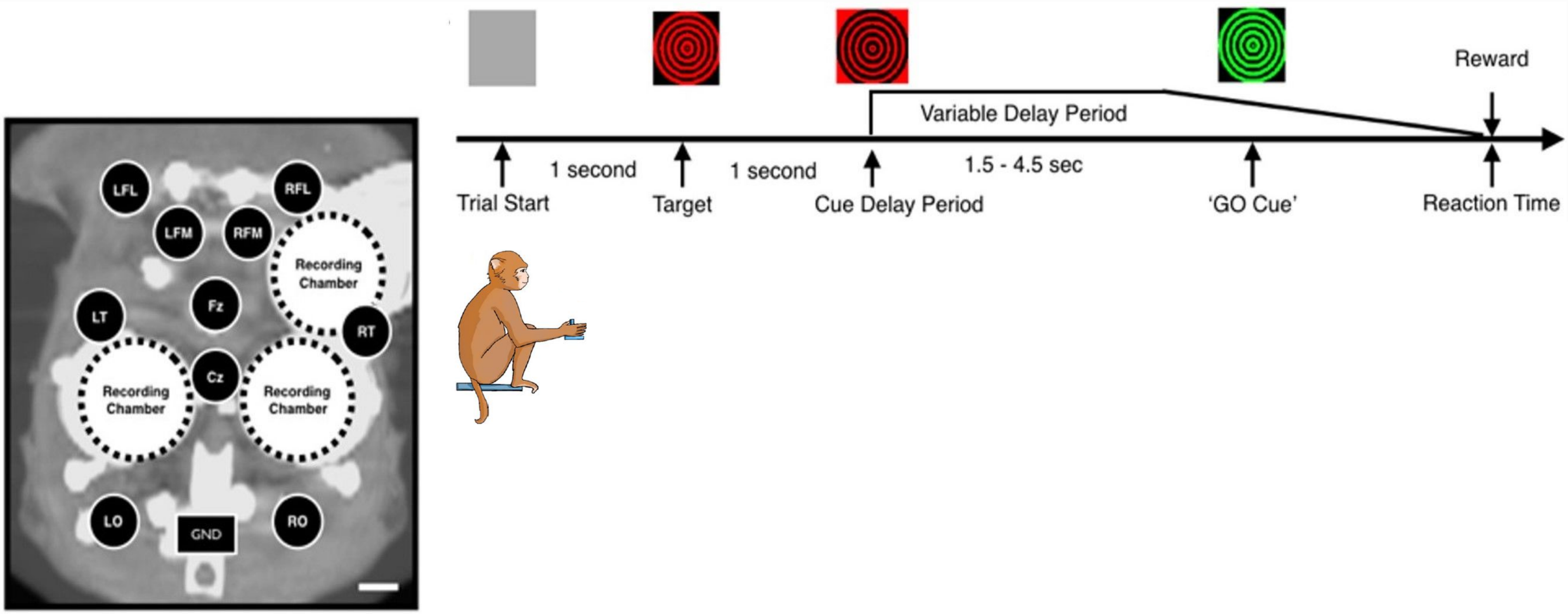
- Deep-brain stimulation (DBS) therapy to restore performance
  - Identify unique **biomarkers of cognitive fatigue** and **drowsiness**
  - **Activate deep-brain stimulation in a closed loop**

Vigilance Task



- Two primates perform a variable delay period reaction-time (VDPR) task

Vigilance Task, ECoG Data



- Two primates perform a variable delay period reaction-time (VDPR) task
- Implanted with a 10-channel epidural **Electrocorticography (ECoG)** array
- Sampling rate of 508.6 Hz
- In total, 129 experimental sessions analyzed (61 for NHP1 and 68 for NHP2)

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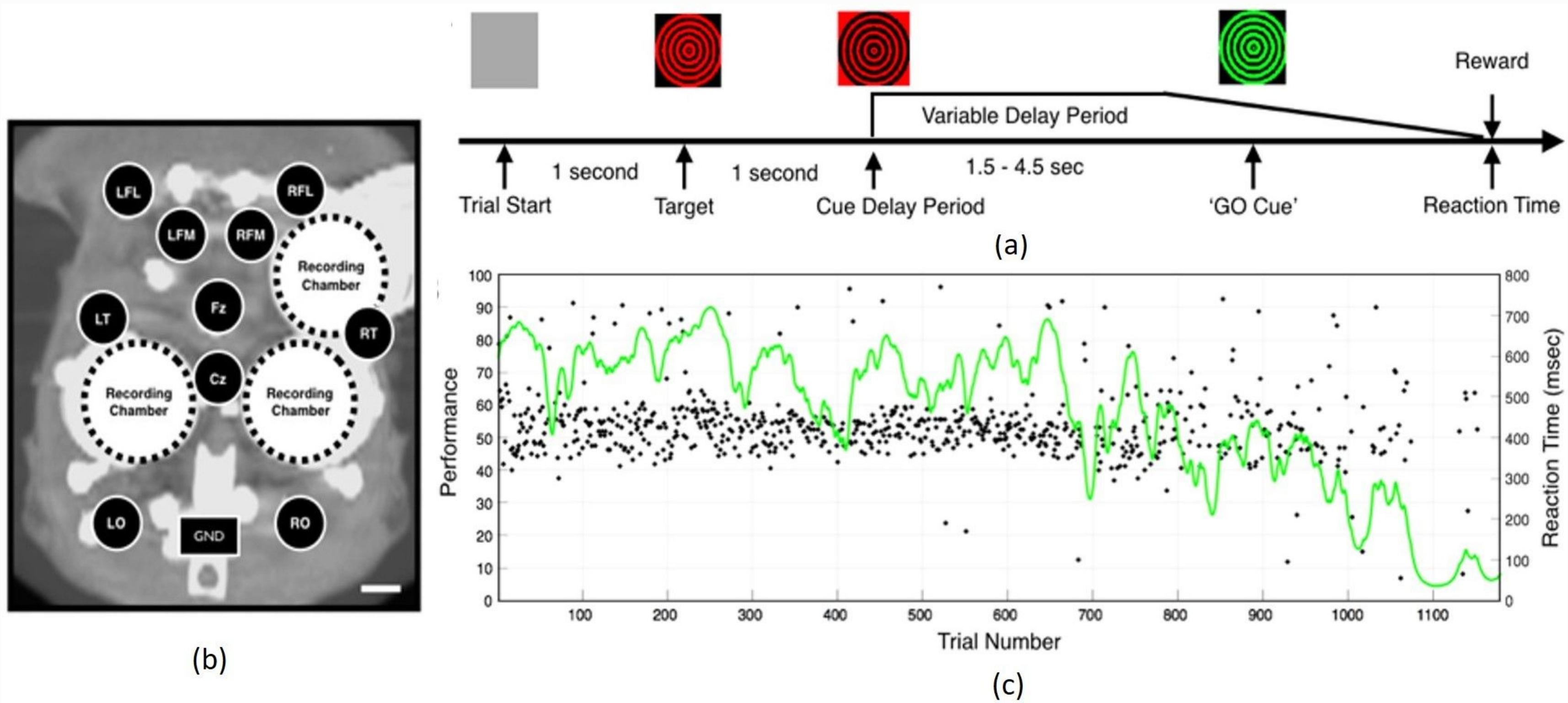


- Performance gradually decreased over time
- One second segments at the onset of delay period used to classify between correct and incorrect trials
- Due to EOG artifacts, frontal electrodes excluded from the analysis

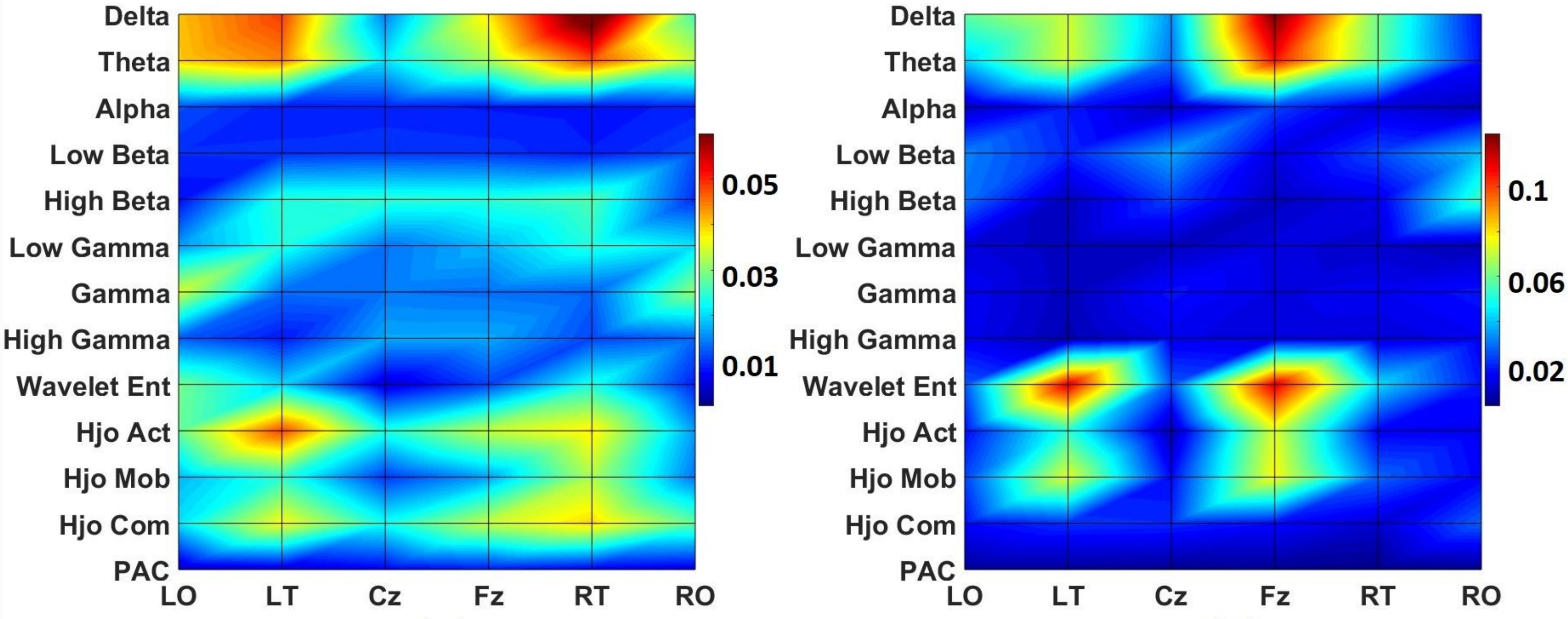
Neural Biomarkers of Fatigue

Feature	Description
1. Delta	Spectral power in (1-4 Hz)
2. Theta	Spectral power in (4-8 Hz)
3. Alpha	Spectral power in (8-12 Hz)
4. Low Beta	Spectral power in (12–20 Hz)
5. High Beta	Spectral power in (20–30 Hz)
6. Low Gamma	Spectral power in (30–45 Hz)
7. Gamma	Spectral power in (60-90 Hz)
8. High Gamma	Spectral power in (100-200 Hz)
9. Wavelet Entropy	$E = -\sum_{i=1}^{n} p_i \ln(p_i)$; p_i is the relative wavelet energy.
10. Hjorth Activity	$var(y(t))$; $y(t)$: input signal.
11. Hjorth Mobility	$\sqrt{\frac{var(\frac{dy(t)}{dt})}{var(y(t))}}$; $y(t)$: input signal.
12. Hjorth Complexity	$\frac{Mobility(\frac{dy(t)}{dt})}{Mobility(y(t))}$

Neural Biomarkers of Fatigue

13. PAC	$\frac{[log(N)-H(P)]}{log(N)}$; N: number of bins dividing the phase, $H(P)$: the Shannon entropy of the amplitude distribution.
14. PDC	$P_{ij} = B_{ij}(f)/\sqrt{b_j^*(f)b_j(f)}$; B: Fourier transform of MVAR model coefficients, b_j: the jth column of B, $*$: transpose and complex conjugate operation.
15. IAIF	Instantaneous amplitude (IA) over delta band, instantaneous frequency (IF) over alpha band, and the ratio of IA and IF.
16. PLI	$\frac{1}{T}\sum_{t=1}^{T} e^{j\Delta\theta_t}$; θ_t: the phase difference between two signals at time t, T: the total trial time.

Neural Biomarkers of Fatigue: R^2 distribution



(a) (b)

- The R^2 distribution across features and electrodes
- Representing the square of Pearson correlation coefficient between a feature and the corresponding label for (a) NHP1, and (b) NHP2

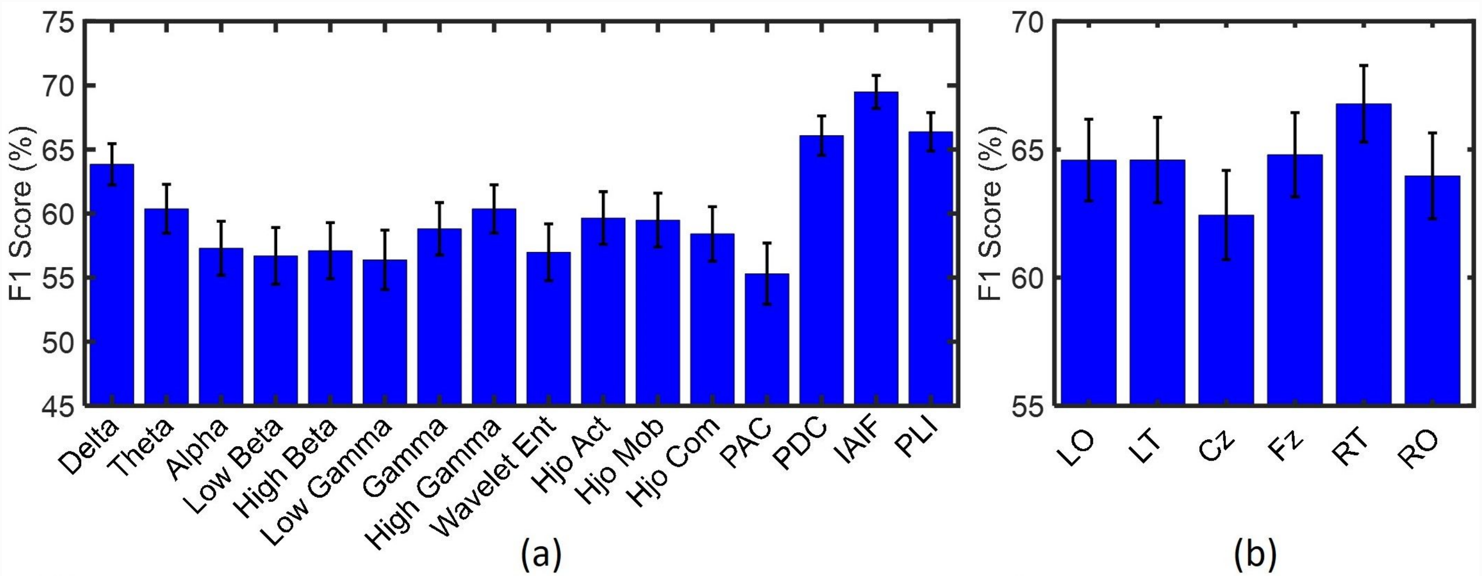
Machine Learning and Feature Selection

- Gradient-boosting decision tree ensemble model (XGB)
  - XGB outperformed classifiers such as linear discriminant analysis (LDA) and support vector machine (SVM)
  - 30 trees with a max depth of 4
  - Unbalanced distribution of correct and incorrect trials: F1 score, as the harmonic mean of sensitivity (TP/(TP+FN)) and precision (TP/(TP+FP))

- A wrapper method used for feature selection

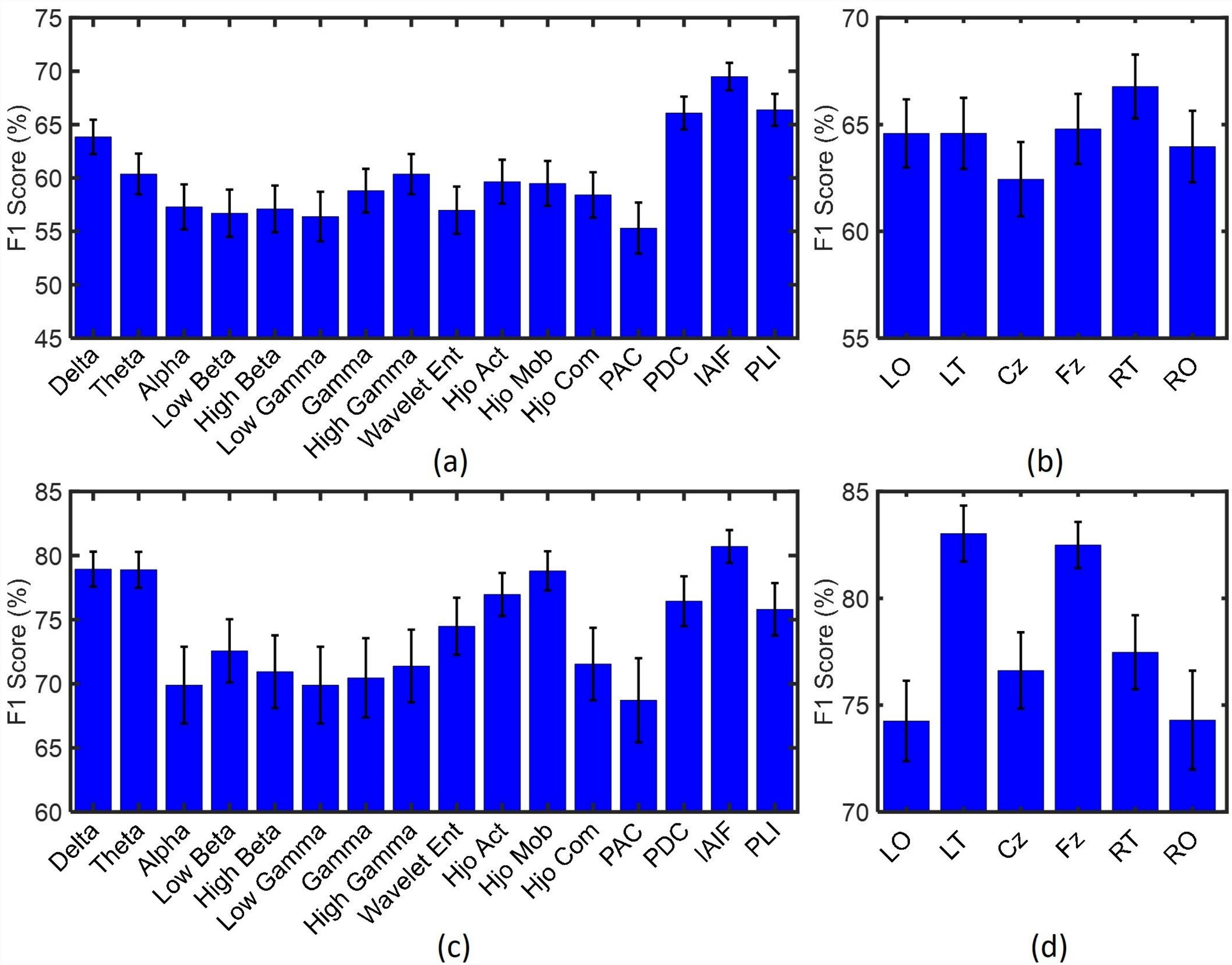
- Performance reported by 5-fold cross-validation

Feature and Channel Importance

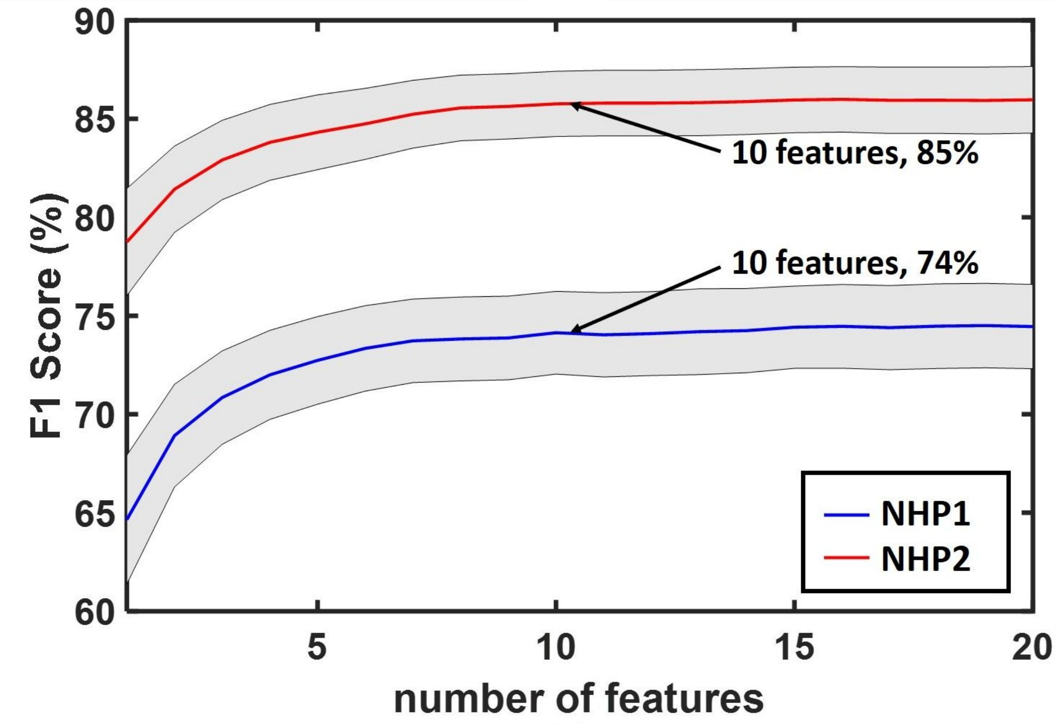


- The one-way ANOVA with repeated measures showed a significant difference among the studied features
- IAIF obtains the highest performance in both NHPs

Feature and Channel Importance

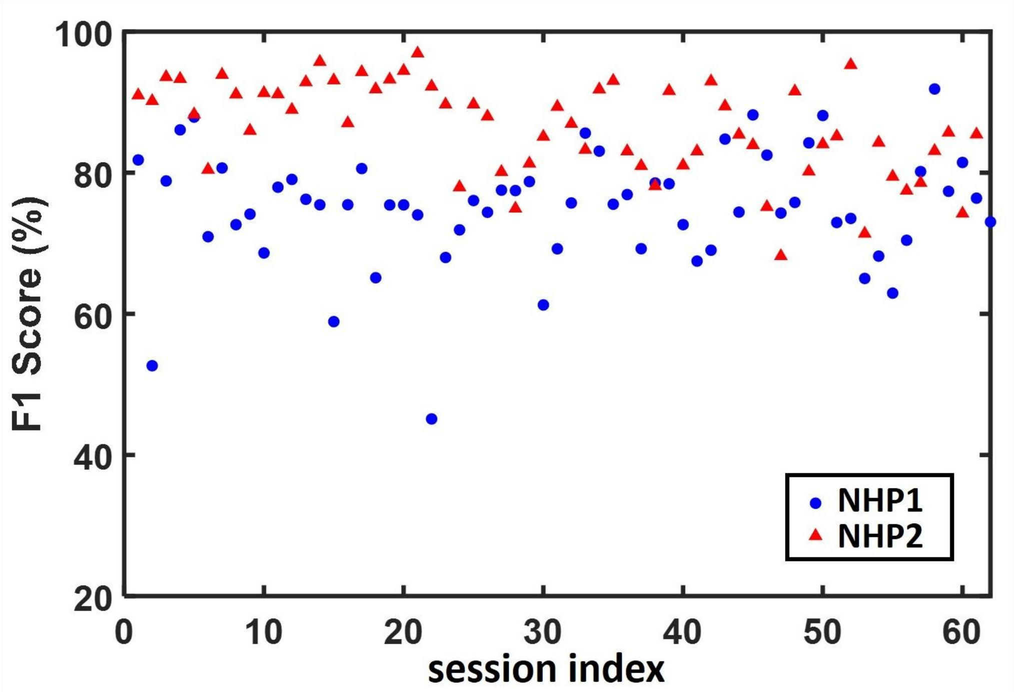


Performance with Feature Selection



- High performance achieved by employing less than 10 features per animal, with PDC being the most useful feature

Performance for Each Session



- Average F1 score of **75.4%±8.4%** and **86.4%±6.6%** for NHP1 and NHP2

Conclusions

- Use of modern machine learning techniques to analyze ECoG from two NHPs
- A vigilance task performed over extended periods of time
- Several features identified to robustly predict performance
- Ultimate goal:
  - Real-time prediction of mental fatigue
  - Guide a responsive therapeutic intervention
  - Restore behavioral performance

Thank you!