What are the best features to decode the levels of working memory load from ECoG data?

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Abstract

This study aims to decode the three levels of working memory load in n-back task (0-back, 1-back and 2-back) from ECoG data, utilising different feature selection strategies using regularised logistic regression. The results demonstrated that feature strategies based on common electrodes across subjects yielded the highest classification accuracies within individualized models, followed by selection of specific brain regions, combined with data-driven methods. We also employed time-frequency analysis to differentiate potential neural markers. The results showed that low-frequency oscillations carried the most discriminative information. Furthermore, our findings indicate that the neural signature of working memory load varies between participants, yet certain cross-participant features appear to be conserved. Overall, effective feature selection may enhance both the interpretation of workload-related neural activity and the performance of simple algorithms.

Keywords: Working Memory; EcoG; n-back; Cognitive Load; Decoding; Supervised Machine Learning

Introduction

Working memory (WM), critically associated with cognitive ability, has been a focal point in psychological research, with numerous paradigms developed to assess it. One notable approach is the n-back test, which has proven effective in measuring varying cognitive load (He et al., 2023). Furthermore, various approaches have been used to examine how the brain encodes information and to uncover the mechanisms underlying working memory (Oberauer et al., 2018); among them, empirical studies using the n-back task have provided significant insights into WM's underlying neural substrates (Zhang et al., 2018; Satake et al., 2024).

One way to investigate these neural substrates in the n-back task is using machine learning (ML) techniques combined with electrophysiological modalities. For instance, the employment of ML algorithms has demonstrated effectiveness in predicting mental workload (Mandal et al., 2020). However, unlike ECoG, EEG has low spatial resolution and is more sensitive to the participant's movements (Erez et al., 2021; Tremmel et al., 2019). Moreover, studies have primarily focused on differentiating between two states of mental load (e.g., 1-back vs 3-back: Zhang et al., 2019).

Working memory load is reflected in specific frequency patterns, which can serve as important neural markers of cognitive demand. Alpha reduction and theta increase have been linked to cognitive workload, with alpha reflecting mental effort and theta correlating with higher task demands, especially in frontal regions during working memory tasks (Pfurtscheller et al., 1996; Klimesch, 1997; Jensen & Tesche, 2002). Delta activity is often associated with attentional effort (Harmony et al., 1996). Together, these findings suggest that changes in alpha and theta bands offer valuable insights into how the brain dynamically responds to varying levels of working memory load.

In the current study, we aimed to decode task difficulty, a proxy for working memory load, from frontoparietal electrocorticography (ECoG) data collected from three subjects during an n-back memory task (0-back, 1-back, and 2-back). Specifically, we assessed the influence of different features, which are electrodes with the highest L2 distances, electrodes in the frontal lobe, and those shared on all subjects, on mental load classification. Additionally, we examine time-frequency dynamics and explore frequency bands that may be significant to decode working memory load. Our study is unique in three ways. First, ECoG provides higher spatial resolution compared to EEG. Second, we explore a range of ECoG-derived features. Finally, ECoG data is rarely used in the existing literature for this purpose, and we demonstrate that simple models with informative features may be sufficient for decoding cognitive load.

Methods

We tested several feature selection strategies to decode working memory load from neural activity in the frontoparietal cortex, achieving above-chance accuracy across three subjects. These strategies included data-driven methods (selecting electrodes with the highest L2 distances between n-back labels, overlapping electrodes across subjects), spatially-driven methods (frontal lobe electrodes and Brodmann area parcellations), and randomly selected electrodes as control. The ECoG dataset (Miller, 2016) was preprocessed by applying a 50 Hz high-pass filter, computing the power envelope, and normalizing the channels. We used regularized logistic regression for decoding, and data is split into trials and divided into 80% training and 20% testing sets. Decoder performance was assessed by measuring the accuracy for classifying task type, i.e., 0-back, 1-back, or 2-back. Model selection used cross-validation to evaluate logistic regression with varying C values (L2 penalty). The best C, yielding the highest average accuracy, was chosen for the final model fitting.

Additionally, we performed Power Spectral Density (PSD) analysis across 64 EEG channels within a 2000 ms window (-400 ms to 1600 ms) relative to stimulus onset, using time-frequency decomposition to examine spectral characteristics under different working memory load conditions (0-back, 1-back, and 2-back).

Results and Discussion

Table 1 demonstrates the accuracy results from the regularized logistic regression model for 5 feature strategies. The use of common electrodes between all subjects revealed the best accuracy result within individualized models of each subject, respectively, 78.33%, 61.67%, and 41.67%, followed by the use of electrodes within the Frontal lobe (65.00%, 68.33%, 26.67%) and electrodes with the highest L2 distances between 0-back, 1-back, and 2-back (65.00%, 61.67%, and 26.67%).

Table 1: Regularized Logistic Regression Model Accuracies corresponding to each feature for three subjects

Features	Subject 1	Subject 2	Subject 3
Electrodes with highest L2 distances between n-back labels	65.00%	61.67%	26.67%
Common electrodes between all subjects	78.33%	61.67%	41.67%
Electrodes from the Frontal lobe	65.00%	68.33%	26.67%
Electrodes from Brodmann Areas	40.00%	66.67%	28.33%
Randomly selected Electrodes	55.00%	64.00%	28.00%

For these three best feature sets, Figure 1A, 1B, and 1C indicate how accurately the model predicted each n-back condition by comparing the true and predicted labels. Both data-driven features (common electrodes) and spatially informative regions (such as the frontal lobe) reveal their potential for classifying working memory load from EcoG data.

Furthermore, the time-frequency analysis revealed that lower frequency bands, delta (0.5–4 Hz), theta (4–8 Hz), and low alpha (8–10 Hz) carried the most discriminative information across all n-back levels. Notably, we observed a significant increase in power following stimulus onset, peaking around 800 ms. This increase was most prominent in the lower frequency range and gradually declined over time, yet it remained distinguishable between the different working memory load conditions. These temporal and spectral dynamics (particularly in alpha and theta bands) support the previous research (Harmony et al., 1996; Pfurtscheller et al., 1996; Klimesch, 1997; Jensen Tesche, 2002) and suggest that early post-stimulus low-frequency activity may serve as a reliable neural marker for decoding working memory load.

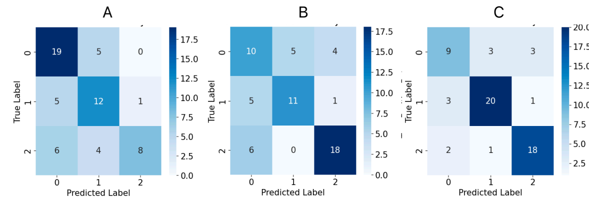

Figure 1: Classification metric: Confusion Matrices for subject 1, A. Electrodes with highest L2 Distances between n-back label B. Only electrodes in Frontal Lobe and C. Commonality of electrodes between all subjects.

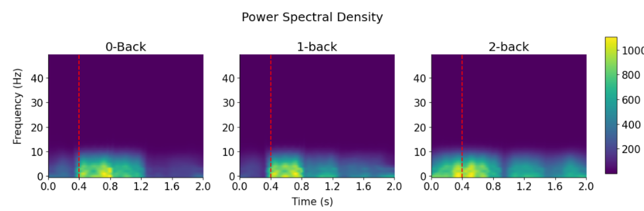

Figure 2: Power Spectral Density of Subject 1 for 0-back, 1-back, and 2-back, respectively. Red lines represents the onset of the stimuli presentation. In the color bar, yellow color represents the highest power spectral density.

Conclusion

This study highlights the importance of feature selection in decoding working memory loads from EcoG signals with simple algorithms. Additionally, low-frequency activity (0–10 Hz), particularly theta and low-alpha, was found distinct across n-back levels. Future work should explore integrating these approaches for fusion models for decoding and expanding the subject pool to develop a more robust framework.

References

Brouwer, A. M., Hogervorst, M. A., Van Erp, J. B., Heffelaar, T., Zimmerman, P. H., & Oostenveld, R. (2012). Estimating workload using EEG spectral power and ERPs in the n-back task. *Journal of Neural Engineering, 9*(4), 045008.

Erez, Y., Assem, M., Coelho, P., Romero-Garcia, R., Owen, M., McDonald, A., ... & Santarius, T. (2021). Intraoperative mapping of executive function using electrocorticography for patients with low-grade gliomas. *Acta Neurochirurgica, 163*, 1299–1309.

Harmony, T., Fernández, T., Silva, J., Bernal, J., Díaz-Comas, L., Reyes, A., ... & Rodríguez, M. (1996). EEG delta activity: An indicator of attention to internal processing during performance of mental tasks. *International Journal of Psychophysiology, 24*(1–2), 161–171.

He, H., Chen, Y., Zhang, X., & Liu, Q. (2023). Working memory capacity predicts focus back effort under different task demands. *Consciousness and Cognition, 116*, 103589.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. *European Journal of Neuroscience, 15*(8), 1395–1399.

Klimesch, W. (1997). EEG-alpha rhythms and memory processes. *International Journal of Psychophysiology, 26*(1–3), 319–340.

Mandal, S., Singh, B. K., & Thakur, K. (2020). Classification of working memory loads using hybrid EEG and fNIRS in machine learning paradigm. *Electronics Letters, 56*(25), 1386–1389.

Miller, K. J. (2016). A library of human electrocorticographic data and analyses. *Stanford Digital Repository*. Available at: https://purl.stanford.edu/zk881ps0522

Oberauer, K., Lewandowsky, S., Awh, E., Brown, G. D. A., Conway, A., Cowan, N., ... Ward, G. (2018). Benchmarks for models of short-term and working memory. *Psychological Bulletin, 144*(9), 885–958. https://doi.org/10.1037/bul0000153

Pfurtscheller, G., Stancak Jr, A., & Neuper, C. (1996). Event-related synchronization (ERS) in the alpha band—an electrophysiological correlate of cortical idling: A review. *International Journal of Psychophysiology, 24*(1–2), 39–46.

Satake, T., Taki, A., Kasahara, K., Yoshimaru, D., & Tsurugizawa, T. (2024). Comparison of local activation, functional connectivity, and structural connectivity in the N-back task. *Frontiers in Neuroscience, 18*, 1337976.

Tremmel, C., Herff, C., Sato, T., Rechowicz, K., Yamani, Y., & Krusienski, D. J. (2019). Estimating cognitive workload in an interactive virtual reality environment using EEG. *Frontiers in Human Neuroscience, 13*, 401.

Zhang, P., Wang, X., Zhang, W., & Chen, J. (2018). Learning spatial–spectral–temporal EEG features with recurrent 3D convolutional neural networks for cross-task mental workload assessment. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 27*(1), 31–42.