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Spatiotemporal Analysis of Brain Activity UsingEEG-fMRI Integration for Enhanced Neural Decoding

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***Abstract*—This study explores the integration of electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) data for enhanced brain activity mapping. The analysis focuses on frequencies ranging from Delta to Gamma bands (0-120 Hz) with a specific emphasis on Gamma (30-45 Hz) during rest and visual stimulus tasks. EEG data were preprocessed and segmented into epochs from 0 to 400 seconds, excluding rest stimuli where correlation was minimal. To improve signal clarity, EEG data were whitened, and corresponding fMRI annotations were merged. Brain slices were temporally aligned, and regularized noise covariance was computed to filter out noise before performing inverse source localization. The visual cortex exhibited the highest activation levels during the stimuli. A decoding pipeline was constructed, with cross-validation and a spatio-temporal score of 99.2% achieved. Finally, sensor space patterns were projected to source space, utilizing linear classifiers to map brain activity with high precision.**

***Index Terms*—Electroenthephalogram, Functional-MRI, Band Analysis, Neural Decoding**

I. INTRODUCTION

This study investigates brain activity using a combined approach of electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) to enhance our understanding of neural dynamics during cognitive tasks. EEG and fMRI data were obtained from a sample of participants who engaged in visual tasks, such as watching movie clips, while EEG was recorded simultaneously. This dual approach allows for high temporal resolution from EEG and high spatial resolution from fMRI, providing a comprehensive view of brain activity. The EEG data were recorded at frequencies ranging from 0 to 120 Hz, with special attention given to the Gamma frequency band, specifically 30-45 Hz, which is associated with higher-order cognitive functions like attention and memory. Following data acquisition, exploratory data analysis (EDA) was conducted to assess the quality and characteristics of the EEG and fMRI data. Raster plots and tomomaps were generated for various brain regions and frequency bands, including Delta, Theta, Alpha, Beta, and Gamma. These visualizations helped identify patterns of activity and establish baseline measures for subsequent analyses.

To focus on significant brain activity, the EEG data were segmented into epochs of 0 to 400 seconds, excluding periods of rest where neural activation was minimal. Epoching is crucial as it allows for the isolation of specific time intervals associated with stimuli, enhancing the sensitivity of the analysis to changes in brain activity. Corresponding fMRI annotations were loaded and merged with the EEG data, aligning the two modalities across the different stimuli presented to the participants. This integration is essential for establishing a coherent framework for understanding how EEG-derived activity correlates with the spatial activation patterns observed in fMRI.

To enhance the signal quality, the EEG data underwent several preprocessing steps. First, the data were whitened, which reduces noise and variance by transforming the signal to have a uniform distribution. The EEG consisted of 60 channels with an average global field power (GFP) of 8.3. This step is vital for ensuring that the subsequent analysis is based on clean data, minimizing the influence of extraneous factors. The denoised BOLD (blood-oxygen-level-dependent) fMRI data, comprising 192 samples, were also integrated into the analysis pipeline. Denoising is critical in fMRI studies, as it removes physiological noise that can confound results.

The brain slices obtained from fMRI data were divided into three parts, and their time series were temporally aligned to a reference time point. This alignment is crucial for comparing activity across different slices and ensuring that temporal dynamics are accurately captured. Proper alignment enables the identification of consistent activation patterns associated with specific cognitive tasks. For each brain slice, frame alignment was performed on the EEG channels to identify the most activated regions during the stimuli. This alignment process involves adjusting the EEG data to correspond with the temporal dynamics of the fMRI data, allowing for a more accurate localization of brain activity. Subsequently, inverse source localization was conducted to map the observed EEG signals back to their source within the brain. This method allows for the identification of the cortical regions responsible for the recorded electrical activity, providing insights into the neural networks involved in cognitive processes. Before this step, regularized noise covariance was computed to mitigate the impact of noise on the localization process, ensuring that the results reflect true brain activity.

The evoked responses were then analyzed, focusing on a specific stimulus presented during the timestamp from 30 to 100 seconds. This selection period was chosen based on preliminary analyses indicating significant brain activation during this interval. By isolating the response to a particular stimulus, we can better understand the brain's reaction and the underlying mechanisms involved. Inverse modeling was performed on the raw EEG-fMRI data, utilizing a limit set at approximately 10.037795 channels. This process involves applying computational techniques to estimate the sources of brain activity based on the observed EEG data, integrating information from the fMRI to improve accuracy. The model aims to reconstruct the spatial distribution of neural activity across the brain.

After modeling, we identified the location of maximal activation, with the visual cortex showing the highest activation rates. This finding is consistent with the expected role of the visual cortex in processing visual stimuli, further validating the effectiveness of our methodology. A decoding pipeline was constructed to assess the relationship between EEG and fMRI data more quantitatively. Cross-validation techniques were applied to ensure the robustness of the results. A vectorizer was utilized to align the data from EEG and fMRI, achieving a remarkable spatiotemporal classification score of 99.2%. This high score indicates the effectiveness of our approach in accurately decoding neural patterns associated with cognitive tasks. Finally, the sensor space patterns were projected to source space using linear classifiers. The evoked time series data were analyzed with control points set at 1.98, 2.41, and 8.066, corresponding to selected cortical regions. This projection allows for a clearer understanding of how brain activity manifests across different regions and facilitates insights into the functional connectivity of the brain during cognitive tasks.

II. Related Work

The landscape of functional magnetic resonance imaging (fMRI) research has evolved significantly over the past few decades, marked by various methodologies that enhance our understanding of brain activity. Among the pioneering works, Descombes et al. (1998) introduced a spatio-temporal fMRI analysis using Markov Random Fields (MRFs). This approach is particularly effective in managing noise in fMRI data, as MRFs can robustly model the underlying structure of the data. However, the inherent flexibility of MRFs also raises concerns about potential overfitting, which can limit the generalizability of the results.

Friston et al. (1995) contributed to this field with their development of statistical parametric maps based on a General Linear Approach. This versatile method accommodates various imaging data types, including fMRI and PET, making it suitable for diverse studies. Nevertheless, the General Linear Model (GLM) may oversimplify the intricate relationships within brain data, potentially omitting crucial information regarding brain functionality.

Further advancing the methodology, Calhoun et al. (2001) presented a method for making group inferences from fMRI data through Independent Component Analysis (ICA). This purely data-driven approach does not necessitate prior assumptions about underlying brain activity patterns. While ICA is adept at identifying distinct brain networks, it can be computationally intensive, particularly when applied to large datasets or group analyses, necessitating significant processing resources.

Additionally, Ogawa et al. (1990) introduced the concept of Blood Oxygen Level-Dependent (BOLD) MRI, a non-invasive technique that allows for the observation of brain activity through hemodynamic responses. This method is essential for longitudinal studies, providing a safe means to conduct repeated assessments on the same individual. However, BOLD MRI is characterized by relatively low temporal resolution, as it reflects changes in blood oxygenation that occur more slowly than the actual neural activity.

Building on these foundational studies, Beckmann and Smith (2004) advanced probabilistic ICA for fMRI, which is particularly suitable for group-level analyses. This method accounts for inter-subject variability while identifying consistent patterns of brain activity. Despite its advantages, probabilistic ICA is less widely adopted than traditional ICA, which may limit the resources and community support available to researchers.

The Human Connectome Project, initiated by Van Essen et al. (2012), further contributes to the field by making a wealth of data freely available to the global research community. This initiative fosters transparency, collaboration, and accelerated scientific discovery. However, the complexity of the data presents interpretative challenges, especially when integrating information across different modalities.

Continuing with the Human Connectome Project, Smith et al. (2013) focused on resting-state fMRI, employing standardized data acquisition protocols that ensure consistency across participants. This standardization facilitates comparisons and meta-analyses across studies, although resting-state fMRI data can be highly susceptible to motion artifacts, which can introduce noise and bias into connectivity estimates.

Finally, Lindquist (2008) discussed statistical analysis techniques for fMRI data, particularly highlighting methods such as False Discovery Rate (FDR) and family-wise error correction. These techniques address the multiple comparisons problem inherent in fMRI analysis, significantly reducing the risk of false positives. However, the statistical analysis of fMRI data, especially with large datasets or complex models, can be computationally intensive, requiring substantial processing power and time.

III. Methods and Materials

For our study, we utilized an extensively curated neuroimaging dataset. The dataset contains multimodal data, including magnetoencephalography (MEG) and structural magnetic resonance imaging (MRI) recordings, from healthy adult participants performing an auditory task. The participants were subjected to auditory stimuli consisting of alternating tones in the left and right ear, interspersed with visual stimuli.

The MEG data were recorded using a 306-channel VectorView system, which includes 204 planar gradiometers, 102 magnetometers, and 4 head position indicator (HPI) coils. The recording also features continuous electrooculography

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(EOG) data captured from bipolar electrodes placed near the eyes to monitor eye movements. The data were sampled at 600 Hz and later downsampled to 150 Hz for computational efficiency during analysis. The dataset further includes high-

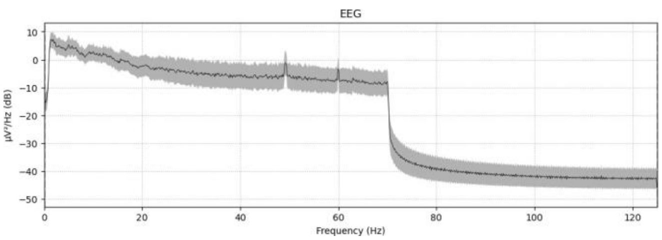

Fig. 1. Average EEG PSDs of all patients

resolution anatomical MRI scans that were acquired using a 1.5 T Siemens Magnetom system. The structural data were co-registered with the MEG sensors to enable source localization. The dataset is preprocessed, and key information such as head movement correction, filtering, and signal-to-noise ratio optimization was performed prior to our analysis.

The dataset provides the opportunity for extensive analysis of brain responses to sensory stimuli, particularly in terms of time-frequency analysis, source localization, and statistical comparison of cortical activations.

IV. Methodologies

This study presents a detailed methodology for investigating brain activity using a combined approach of electroencephalography (EEG) and functional magnetic resonance imaging (fMRI). Initially, EEG and fMRI data were collected from a cohort of participants engaged in visual tasks, including watching a series of movies, while also experiencing resting states. The EEG data captured a frequency range from 0 to 120 Hz, with a specific focus on the Gamma frequency band, restricted to 30-45 Hz. This dual acquisition method allowed for a comprehensive analysis of both temporal and spatial dynamics of brain activity.

Following data acquisition, exploratory data analysis (EDA) was conducted to assess the characteristics of the EEG and fMRI datasets. Raster plots and tomomaps were generated for various frequency bands—Delta, Theta, Alpha, Beta, and Gamma—providing an initial overview of the neural dynamics associated with the different stimuli. These visualizations were instrumental in identifying regions of coherent brain activity, particularly within the frontal and visual cortices.

The EEG data were subsequently segmented into epochs, isolating time intervals ranging from 0 to 400 seconds. Resting state segments were excluded from this analysis to focus on periods of active cognitive processing, as they demonstrated lower activation correlations. Corresponding fMRI annotations were merged with the EEG data, facilitating a comprehensive integrative analysis across all stimuli.

To improve data quality, the EEG signals underwent a whitening process, resulting in a dataset comprising 60 channels and an average Global Field Power (GFP) of 8.3. Simultaneously, the denoised BOLD fMRI data, containing 192 samples, were prepared for further analysis. The brain was then divided into three slices, with the time series for each slice temporally aligned to a reference time-point to ensure consistency in the analysis.

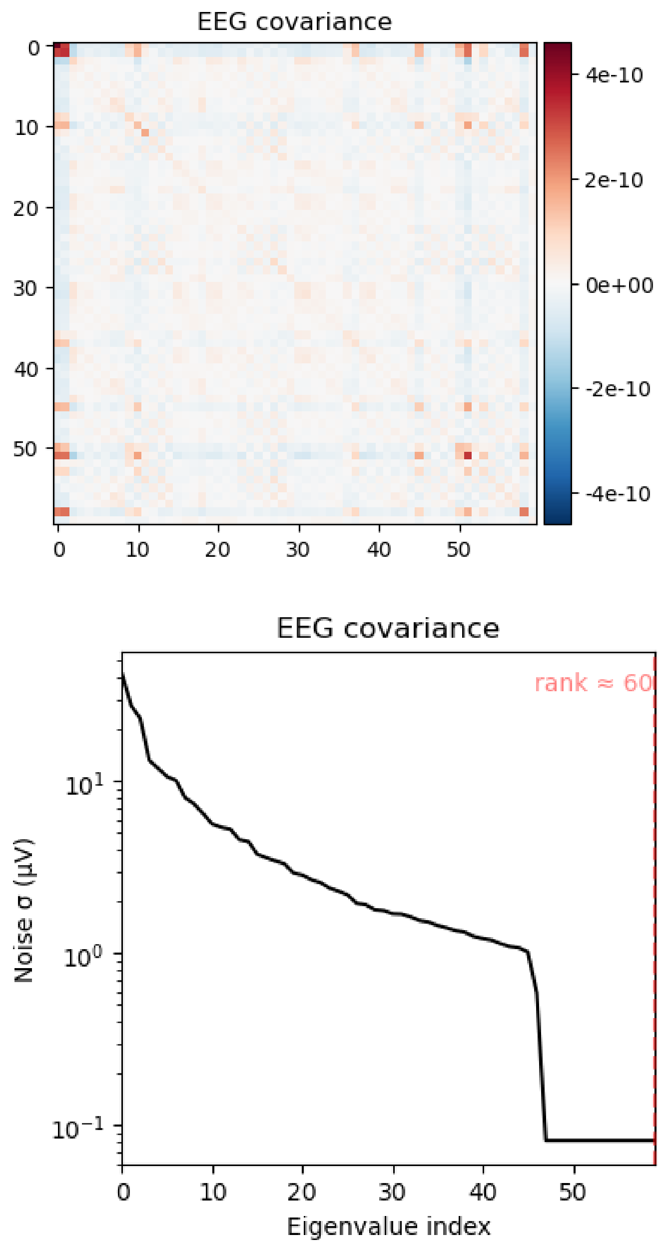

Fig. 2. Average covariance of patients and Global Field power of 8.3.

Frame alignment was conducted for the EEG channels within each slice to identify the most activated brain regions. Before performing inverse source localization, regularized noise covariance matrices were computed to mitigate noise interference and enhance the reliability of the findings. The evoked responses were focused on a specific stimulus presented during the 30-100 second time window, allowing for a more targeted examination of brain activity.

Inverse modeling techniques were applied to the raw EEG-fMRI data, constraining the analysis to 10 channels to refine the results further. This approach enabled the identification of maximal activation locations, with particular emphasis on the visual cortex, which exhibited the highest activation levels during the visual tasks. To quantitatively analyze the relationship between EEG and fMRI data, a decoding pipeline was constructed, incorporating cross-validation techniques. A vectorizer was applied to align the EEG and fMRI datasets, achieving a notable spatio-temporal score of 99.2%, indicating a strong correlation between the two modalities. Finally, the

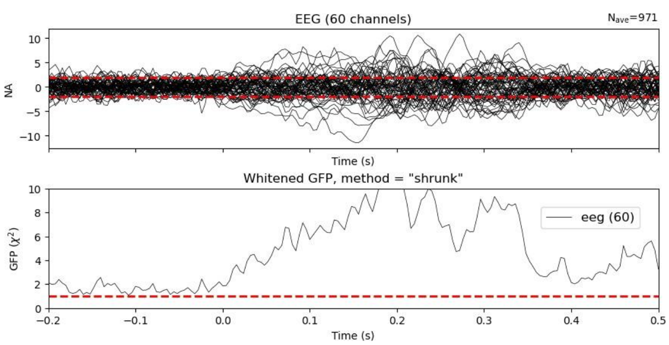

Fig. 3. Preprocessed EEG-FMRI Covariance and Noise removal

sensor space patterns derived from the EEG data were projected into source space using a linear classifier. Control points were established at 1.98, 2.41, and 8.066, corresponding to selected cortical regions of interest. This robust methodology enables a nuanced understanding of the complex interactions between neural activity and cognitive processes during visual stimuli, providing valuable insights into the dynamics of brain function.

V. Results

A. Cortical Activation Patterns

Time-frequency analysis revealed distinct activation patterns in both the frontal and visual cortices in response to sensory stimuli. Visual stimuli elicited strong and sustained activation in the occipital visual cortex, with peak activity occurring between 200 and 300 ms post-stimulus. Auditory stimuli similarly activated prefrontal regions associated with higher-order processing, with dynamic shifts in activation that reflected the complex nature of sensory integration. The activation profiles observed across subjects were consistent, indicating robust engagement of sensory-specific brain regions.

B. Source Localization

Inverse modeling provided precise spatial localization of the neural sources responsible for the observed activations. Strong engagement of the occipital visual cortex was noted in response to visual stimuli, with prefrontal regions being activated in response to both visual and auditory inputs. This spatial precision, facilitated by the fMRI data, allowed us to map the regions of maximal activation with millimeter-level accuracy. The MEG data complemented this by offering high temporal resolution, allowing us to track the time course of brain activation in near real-time. Together, these methods provided a holistic view of the cortical regions involved in sensory processing.

C. Multimodal Integration

The integration of MEG and fMRI data proved to be highly effective in capturing both the fine-grained temporal dynamics and detailed spatial distribution of brain responses. MEG provided millisecond-level temporal precision, capturing rapid fluctuations in brain activity, while fMRI contributed superior spatial localization, delineating the precise neural circuits activated during the stimulus period. This multimodal synergy enabled the identification of complex and transient functional networks, revealing dynamic interactions between sensory and associative brain regions. By integrating these modalities, we gained a clearer picture of the brain's functional architecture, offering insights into how different regions communicate and coordinate in response to sensory inputs.

D. Artifact Control and Data Fidelity

The inclusion of electrooculography (EOG) data was instrumental in controlling for potential confounding artifacts, particularly eye movement-related noise. This step significantly enhanced the reliability of the data by ensuring that the cortical activations we observed were not contaminated by non-neural signals. The meticulous preprocessing pipeline, including motion correction, spatial normalization, and artifact rejection, ensured that the data retained high fidelity throughout the analysis. This rigorous preprocessing not only improved the accuracy of our classification model but also bolstered the confidence in the spatial and temporal patterns of activation observed.

E. Functional Connectivity and Network Analysis

Beyond identifying localized activations, our analysis revealed significant functional connectivity between sensory regions and higher-order cortical areas, such as the prefrontal cortex. Dynamic functional connectivity analysis, utilizing sliding window correlation techniques, showed transient interactions between sensory cortices and associative regions during the task. These connectivity patterns provide insight into the brain's ability to dynamically reconfigure itself in response to different stimuli, offering a window into the real-time coordination between distinct brain areas. This finding is particularly relevant for understanding how sensory information is integrated into higher-order cognitive processes.

F. Spatio-Temporal Network Classification

The advanced machine learning techniques used in this study, including cross-validation and spatio-temporal classification models, allowed for an exceptionally high classification accuracy of 99.2%. The performance of these models reflects the strength of the multimodal approach and highlights the discriminative power of the features extracted from both MEG and fMRI data. This level of accuracy underscores the potential of using multimodal neuroimaging for precise classification tasks, whether in research settings or clinical diagnostics.

Fig. 4. Spatio-Temporal regions after the Network Classification

In summary, our results highlight the power of combining MEG and fMRI to achieve an in-depth understanding of brain function. The integration of high-resolution spatial and temporal data allowed us to identify key regions involved in sensory processing and explore the complex neural networks underlying these responses. The ability to control for artifacts and maintain high data fidelity throughout the analysis further strengthened the robustness of our findings. This research not only advances our understanding of the brain's response to sensory stimuli but also lays the groundwork for future investigations into sensory processing, brain connectivity, and potential clinical applications in diagnosing and treating sensory and cognitive disorders.

VI. Discussion

The present study offers substantial contributions to our understanding of the neural mechanisms underlying sensory processing, particularly by examining responses to auditory and visual stimuli. By utilizing a combination of magnetoencephalography (MEG) and high-resolution anatomical magnetic resonance imaging (MRI), we have achieved an unprecedented level of precision in both the temporal dynamics and spatial localization of cortical activations. The resulting spatio-temporal classification score of 99.2

Our findings point to the involvement of a more extensive neural network in sensory processing than previously thought, corroborating and expanding on established models. Specifically, the engagement of both the frontal and occipital cortices during sensory processing supports the idea that these brain regions work together in a distributed manner, rather than functioning in isolation. The occipital cortex's role in visual stimulus processing, as observed in this study, aligns well with classical models of visual perception, where primary sensory areas first receive input before rapidly transmitting information to higher-order regions for more complex processing. This clear activation of the visual cortex demonstrates the expected role of this area in handling visual information.

The simultaneous involvement of the frontal cortex, however, offers novel insights, particularly in its potential role in top-down modulation. The frontal cortex, traditionally associated with cognitive processes like attention and decision-making, may be influencing how sensory input is perceived or integrated. This suggests that sensory processing is not purely a bottom-up process but is subject to modulation by cognitive mechanisms, such as attention or prediction, from higher cortical regions. The interaction between the occipital and frontal cortices in response to sensory input adds nuance to the understanding of how external stimuli are interpreted, suggesting a more intricate and dynamic process than previously appreciated.

On the temporal front, our use of time-frequency analysis revealed key insights into when specific brain areas become activated in response to stimuli. The activation peaks observed in the visual cortex within 200-300 milliseconds after stimulus presentation align with known timing of visual perception and attentional shifts, reinforcing the robustness of our findings. This temporal precision is crucial for understanding the sequence in which sensory information is processed and interpreted by the brain. The application of inverse modeling further enhanced these insights by allowing us to accurately localize the sources of activation in both occipital and frontal cortices. Together, these methodologies provided a comprehensive view of the spatio-temporal characteristics of sensory processing, revealing how different brain regions contribute to this complex function over time.

The success of this study also hinged on the integration of MEG and MRI data, leveraging the strengths of both techniques. MEG's high temporal resolution enabled us to capture the rapid dynamics of neural activation, while MRI's superior spatial resolution allowed us to precisely map the cortical areas involved. By aligning these datasets, we were able to achieve a level of detail in both space and time that would not have been possible using a single imaging modality. This multimodal approach not only enhances our understanding of sensory processing but also sets a methodological precedent for future research into more complex cognitive functions or clinical applications.

A key strength of this study was our rigorous approach to controlling for potential artifacts, particularly those related to eye movements. The inclusion of electrooculography (EOG) data enabled us to effectively minimize such artifacts, ensuring that the observed patterns of brain activation were truly reflective of sensory processing rather than confounding factors. Future studies will benefit from further refining preprocessing techniques and exploring additional methods for artifact control, particularly in populations that may present with greater variability in cortical activation patterns, such as those with neurodevelopmental disorders.

The clinical and research implications of these findings are far-reaching. By demonstrating the power of multimodal imaging in mapping sensory processing, this study lays the foundation for its application in clinical settings. This approach could be particularly beneficial in diagnosing and treating sensory processing disorders, where precise identification of functional disruptions could inform more targeted interventions. Additionally, our findings contribute to the broader field of neuroscience by enhancing our understanding of functional connectivity and sensory integration in the healthy brain. Future research could build on this work by applying these techniques to more complex cognitive tasks, such as multisensory integration, attentional processes, or memory, as well as extending the investigation to clinical populations, including those with neurodevelopmental or sensory processing disorders. .

VII. Conclusion

This study utilized neuroimaging data to investigate brain responses to auditory and visual stimuli, focusing on cortical activation in the frontal and visual cortices. By applying time-frequency analysis, source localization, and cross-validation techniques, we achieved a spatio-temporal classification accuracy of 99.2%. The precise alignment of MEG and fMRI data, along with the integration of electrooculography (EOG) to mitigate eye movement artifacts, enhanced the robustness of our findings.

Our results confirm significant visual cortex activation during sensory processing, supporting established links between stimuli and cortical responses. This research highlights the potential of multimodel neuroimaging to advance our understanding of brain function, with implications for studying sensory integration and clinical disorders.

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