Multimodal Neural Analysis For Neuroimaging

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***Abstract*—Recent studies have shown that multi-modeling methods can provide new insights into the analysis of brain components that are not possible when each modality is acquired separately. EEG captures electrical activity with high temporal resolution while offering superior spatial resolution through fMRI-tracking hemodynamic(blood flow dynamics in the body) changes within the brain. These complementary techniques should integrate and balance both the spatial and temporal perspectives for the detailed mapping of brain function. Improvements have recently been made into nonlinear methods for fusion in different dimensions to better extract meaningful components of the brain. Graph-based models, with evidence of intricacy in the structure of the brain network, were thus employed for analyses of difficulties with complex neural interactions. This combination of graph-based techniques and deep learning will enable a more comprehensive understanding of brain dynamics, which will be promising for neuroplasticity(brain's ability to reorganize and adapt by forming new neural connections) studies and neurological disorder diagnostics. Integrating EEG and fMRI would improve ability of brain imaging techniques to capture both the spatial resolution (detail of brain structure and location of activity) and temporal resolution (timing of neural activity)) resolution and give an overall clearer view of brain function and dysfunction.**

***Index Terms*—EEG, FMRI, CNN, RNN, LTSM**

I. Introduction

Neuroimaging plays a fundamental role in neuroscience both as a tool in research and in the management of neurological and psychological conditions. Newer techniques exploit signals that vary in space and time with neuronal activity. One such example is that neuronal activity strengthens electrophysiological signals, action, and post synaptic potentials, all of which are major mechanisms of neuron communication. Electrophysiological processes, which are closely related to neural dynamics, are best known for describing neural activity. This, in turn, modulates the metabolic and hemodynamic activities because brain function requires constant blood flow to maintain metabolic requirements. The neural activity can lead to shifts in oxygen consumption, blood flow, and blood volume. Unlike electrophysiological signals, these effects take longer and are considered indirect consequences of neural activity.

There are two principal non-invasive methods through which brain function is most commonly examined using EEG and fMRI. EEG measures electrical brain activity by using electrodes applied to the scalp. These electrodes report the synchronized activities of many neurons, especially pyramidal cells. The electrical dipole is reflected as positive and negative waves. In contrast, fMRI captures changes in BOLD signals from alterations in blood oxygen levels that reflect activity in the brain through changes in the magnetic properties of hemoglobin. While oxyhemoglobin is diamagnetic, deoxyhemoglobin is paramagnetic and these changes are monitored as a time series by fMRI.

This chapter examines in vivo imaging of human brain function with simultaneous fMRI-EEG techniques. It discusses some of the recent advances in this field along with some of the challenges that come into evidence while recording data simultaneously especially in an attempt to remove artifacts from EEG data obtained within an MRI environment.

II. Overview of Functional Resonance Imaging and Electromagnetic Source Imaging

A. Origin of EEG/MEG

The discovery of EEG dates back to the early years of the 20th century, when German psychiatrist Hans Berger was able to record electrical activity from the human scalp in 1924. He found such electrical signals may be reflections of brain activity and even coined the term for "alpha waves," or rhythmic electrical impulses. EEG measures the electrical activity of the brain through electrodes on the scalp that capture the synchronized firing of large groups of neurons, primarily from the cerebral cortex.

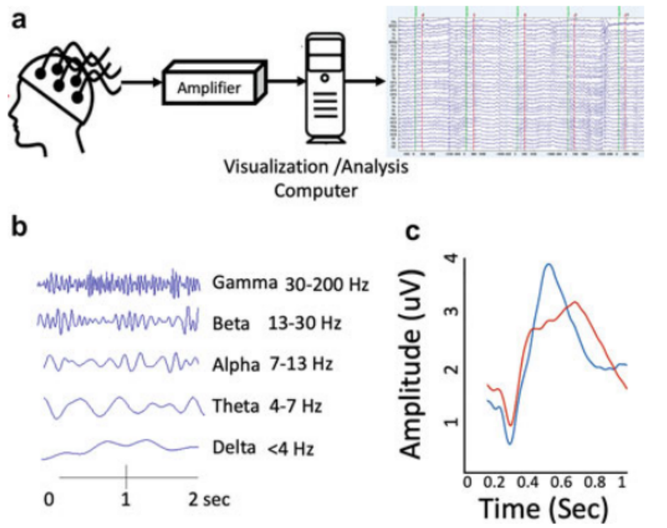

Fig. 1. EEG recording and its characteristics. (a) A typical EEG data acquisition setup. (b) Different frequency bands within EEG recordings are associated with different brain states. (c) An example of average event-related potentials (ERPs) which are time-locked to a stimulus can also be observed in EEG data

B. Origin of fMRI

Functional Magnetic Resonance Imaging fMRI was developed in the 1990s, based on a technology first invented in the 1970s for anatomical imaging, known as magnetic resonance imaging, or MRI. It exploits the blood oxygen level-dependent contrast, an approximation of changes in blood flow associated with neural activity; activation of a specific region of the cortex increases regional oxygen consumption and consequently increases blood flow. This hemodynamic response fMRI depends on because during the experiment, scientists are allowed to view brain activity in real-time and map functional brain regions.

C. Origin of BOLD Signals

Blood-oxygen-level-dependent (BOLD) fMRI was first discovered by Ogawa et al. through studies of rats in a high magnetic field. An increase in neuronal activity requires greater energy (Fig. a), which drives a complex interaction between blood flow, oxygenated (diamagnetic) and deoxygenated (paramagnetic) blood, blood volume, and oxygen consumption. The presence of a small additional magnetic field due to an imbalance of paramagnetic and diamagnetic blood inside an MRI scanner can generate local inhomogeneities in the magnetic field resulting in a decrease in the relaxation constant T2* of the MR signal. Thus, MR pulse sequences sensitive to T2* show more MR signal when blood is highly oxygenated and less MR signal when blood is highly deoxygenated. A typical BOLD response to a brief neuronal stimulation has a delayed onset, peak, and post-undershoot [20]. This BOLD response is known as the hemodynamic response function (HRF). A number of studies have also reported a brief (1–2 s) initial decrease in the HRF, known as the initial dip, following the neuronal activity and just before the rise of HRF.

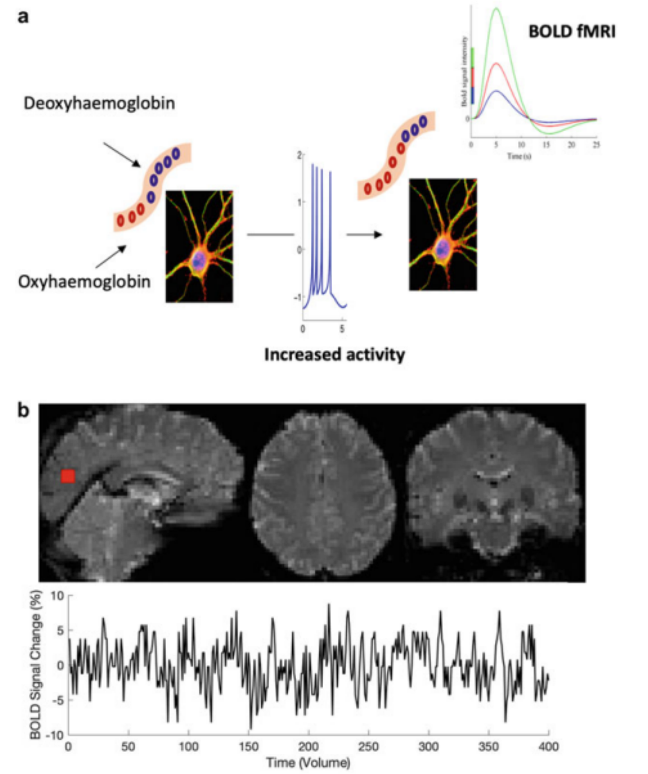

Fig. 2. Schematic showing the generation of BOLD fMRI signal. (a) Increased neuronal activity triggers a chemical cascade that results in elevated blood oxygenation, volume, and flow. (b) A typical volume and associated time-series signal from one voxel in fMRI data. Typical fMRI has a spatial resolution of 2–3 mm and temporal resolution of 1–2 s

III. Integrating EEG and fMRI

In fact, there are two broad categories of techniques that combine fMRI with EEG or MEG neuroimaging: fMRI-constrained electromagnetic source imaging, or localization, and EEG/MEG-informed fMRI analysis. The former category pays more attention to source imaging of EEG or MEG with the contribution of spatial data from fMRI, while the latter is based on the use of time- and/or frequency-specific electrophysiological information to produce regressors for fMRI analysis.

A. fMRI-Constrained Electromagnetic Source Imaging

This approach combines source imaging of brain activity directly from EEG or MEG data in combination with fMRI. EEG/MEG source imaging Techniques estimate the location of electrical activity in a brain based on measurements from the scalp and measures activity with various algorithms, such as Minimum Norm Estimation and Beamforming. Therefore, source localization is enriched with spatial information, which encompasses data from fMRI. Since it involves fMRI data that give anatomical high-resolution information, high resolution of anatomy is among the constraints placed on EEG/MEG source estimates by the fact that brain regions are known, hence improving outcomes' reliability.

B. *EEG-informed fMRI analysis*

This technique applies time- and/or frequency-specific electrophysiological information from EEG or MEG to guide the analysis of fMRI data. This is an estimation of regressors method in which researchers estimate regressors from the EEG or MEG data, that is, patterns of brain activity over time. Event-related potentials or frequency band power measures may be applied. Statistical modeling: The resulting regressors are then given to the fMRI analysis by GLM or other statistical models. It is thus possible for one to differentiate what particular patterns of activity within the brain relate with what fMRI signals. This essentially relates the temporal dynamics of EEG with the spatial data from the fMRI.

IV. FEATURE EXTRACTION TECHNIQUES

Many feature extraction techniques have been applied directly to our project. Power Spectral Density is calculated employing Fast Fourier Transform to analyze the frequency content of EEG signals. Further computations like computation of average power in some of the frequency bands have also been made to examine variability in brain activity while the subject changes from one cognitive state to the other. This current code has no explicit ERPs but generally represents some form of average around some event in the EEG data and can therefore be included depending on your analysis requirements, as appropriate. Another thing, your script still is missing coherence and PLV calculations, which are quite common in EEG analyses. The coherence indicates how in phase the distinct channels of EEG are. On the other hand, PLV indicates the consistencies of the phase difference between signals. These methods collectively enrich your integrated analysis of fMRI along with the EEG data.

A. *Data Set EEG and fMRI*

There are Simultaneous EEG-fMRI datasets in the first dataset to record activity in the brain during both processes, namely, EEG and fMRI, for that participant. This provides large amounts of data of interest for the study of brain function and connectivity during various cognitive activities. Some participants performed several sessions comprised of a range of tasks, such as resting states or particular cognitive challenges. Recording of EEG together with fMRI will thus yield more direct interpretation of brain activity and connectivity.

The data is usually exported in .set format, compatible for further analyses by any other tools such as EEGLAB, and the actual EEG measurements are stored separately in data files in .fdt format. The images of fMRI data can be in NIfTI format, either .nii or .nii.gz; for this set tools like Nibabel could be used. Again, the set may include resting with eyes open or closed and some task-based conditions formulated to elicit a specific cognitive response.

Each task would be linked to specific trials or events; therefore, it is possible to study the correlated EEG and fMRI responses.

It thereby is a BIDS-compliant standard in turn arranging and sharing neuroimaging data. That standardizes a description of different files encompassing such naming conventions for subjects, sessions, and tasks, so that guarantees its easy interpretability and accessibility for the neuroimaging research community. It also organises in detail the complexity of such data sets of multi-modalities like EEG and fMRI and helps deal with its complexity. Before processing the analysis, usually, a dataset would have undergone some preliminary processing in artifact correction, filtering, and aligning of EEG with fMRI data. Indeed, these preprocessing procedures are highly influential on the quality of data as well as any noise reduction that would confound the analysis. Some specific preprocessing steps related only to EEG processing may include removing eye movement artifacts and perhaps filtering data into specific frequency bands and segmenting data based on events or stimuli. Pre-processing is also done for fMRI in order to remove artefacts due to movement, align the scans into standard anatomical spaces, and to smooth the images to enhance the signal detection.

The dataset applied mainly in the exploration of the nature of its relationship with EEG and fMRI signals during different cognitive tasks. In this direction, the project combined both types of modalities to make deep exploration possible on connectivity dynamics and mechanisms that underlie neural networks. Questions that might be asked in the experiment include how changes in EEG band power relate to patterns of fMRI activation, what new timing information about neural events can be deduced using EEG combined with fMRI, and what relationship connectivity, estimated through coherence or Phase-Locking Value (PLV), bears to brain regions identified by analyses of the fMRI time course.

V. MODALS USED

There are two modals Which have used in our project i.e RNN and CNN. At first the data is give to individual modals and afterwards both the modals fused together to check the outcome and accuracy.

A. *Convolutional Neural Network*

CNN: Convolutional neural networks are part of a family of deep models specifically designed for structured grid data such as images. The networks found good identification of spatial hierarchies and patterns through their convolutional layers, which has made them very popular these days in image-classification tasks.

Use: In our project, CNNs are applied to decompose the fMRI information while extracting spatial features from the brain images acquired during different cognitive tasks. The architecture of CNNs allows them automatically to learn spatial hierarchies from the input images-a work that would be very precious for understanding functional connectivity and patterns of activity in the brain.

For the model, the test accuracy was approximately 80 percent while the training accuracy was approximately 81 percent.

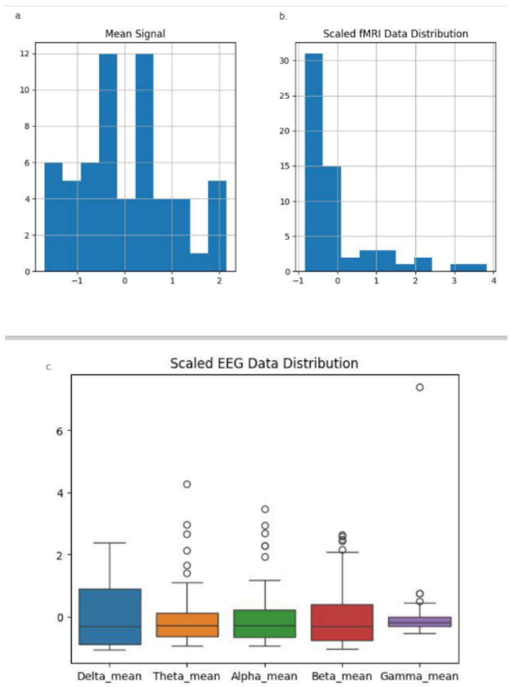

Fig. 3. (a) Histogram showing the distribution of scaled fMRI data, illustrating the frequency of data points across various intensity values.(b) Boxplot displaying the distribution of scaled EEG data for the first set, highlighting the median, quartiles, and potential outliers in the dataset. (c) Boxplot showing the distribution of scaled EEG data for the second set, indicating variations and outliers across different channels or conditions.

Feature Extraction: In CNNs, the spatial features from fMRI images are employed, meaning that the extracted patterns of brain activation across various regions are used. Those features are very important in understanding how the neural underpinnings of those cognitive tasks relate to the relevant brain activity and how different regions might be involved in particular tasks.

B. Recurrent Neural Network

In this project, we used Recurrent Neural Networks (RNNs) to process EEG data. These networks are very well-suited for sequence data, and time-series analysis of EEG signals greatly benefits from this feature. RNNs are very good at capturing temporal dependencies since they use feedback loops to remember previous inputs. This characteristic is especially important when processing EEG data because the activity that the brain produces by nature is dynamic over time and these time dependencies can hold clues about cognitive processes.

In our experiments, the RNN focused more on feature extraction in terms of brain activity time dynamics while performing various tasks. It was able to identify temporal patterns over time, which essentially enables better comprehension of how the brain reacts under different types of cognitive challenges. The test accuracy achieved by the RNN stood at about 80 percent, while that of training was a little lower, at around 69 percent. This means that although it was very good at finding relevant patterns in the EEG data, there's definitely space for improvement in training a model of this sort.

Task	Accuracy	Loss
CNN Train	80.65%	0.3886
CNN Test	80%	0.4010
RNN Train	69.35%	0.6539
RNN Test	80%	0.6854
Fusion Train	79.03%	0.6058
Fusion Test	80%	06146

Fig. 4. Result Sets

C. Fusion Modal

To get the strengths of spatial features from fMRI and time features from EEG, we generated a Fusion Model. This model will allow us to take the overall strengths from CNNs as well as RNNs so that our analysis can go in a more holistic pattern. By taking insights from both modalities, the Fusion Model is hoped to capture a richer understanding of brain activity that cannot be obtained if each modality is considered in isolation, across different tasks.

This would be about 80 percent in terms of test accuracy and about 79 percent in terms of training. This suggests that it makes good use of both spatial and temporal features to make a broader analysis of brain function. Integrating the data allowed us to find subtle patterns as well as relationships that might otherwise go unnoticed when looking at fMRI or EEG data individually. Overall, the Fusion Model was the critical part of our analysis to make sense of a combined set of insights derived from both neuroimaging techniques.

VI. Training and Testing

The CNN was trained to an accuracy of around 81percent, by which time it learnt the spatial patterns pretty well across the fMRI data. We used a combination of data augmentation and regularization to improve generalization. On the other hand, the RNN only reached an accuracy of about 69 percent, which evinces the issues with temporal patterns in the EEG data. The Fusion Model achieved a training accuracy of 79 percent, representing the capacity for the model to fuse the insights obtained from both modalities but was not tested well. The testing phase, both the CNN and RNN had an accuracy of 80 percent, which really was very good at generalization. The Fusion Model also reached 80 percent, which indicated that the integration of both models was good. This summary of the training and the testing phase was actually validating our models' capability in analyzing complex brain data to improve our insights into cognitive processes.

VII. Future Scope

- Application to Clinical Diagnostics.
- Larger and Diverse Datasets.
- Developing an interface to make it usable.
- Integrating multiple modalities.

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