| PROJECT INFORMATION | | | |
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| **Report Description:** | Literature review for EEG signals | | |
| **Professor:** | Prof. [Gady Agam](mailto:agam@iit.edu) | **Tools used/work done:** | 1. Literature Review on EEG 2. Got data acess |
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Work done:

1. Got the data access.
2. Literature review for the new problem statement:

**Classification of Motion States Using EEG Data Collected During a Virtual Construction Site Examination**

**Data:** EEG exam data

From the dataset of EEG signals we can classify 4 different states:

1. **Active Tasking** – In motion to do task
2. **Response Mode** – Answering the question
3. **Cognitive Impasse** – Confused or feeling stuck
4. **Uncertain Response** – Marking the answer as uncertain to answer

**Procedure:**  
  
1. Take the EEG data and split them into the small time frames we need to process the signals by removing the instruction parts.

2. Select the electrodes to coordinate towards the muscle movement actions:

3. Preprocessing the EEG data:

Following data collection, the collected EEG data undergoes preprocessing in EEGLAB. This preprocessing involves several steps, including re-referencing the data, removing artifacts using Independent Component Analysis (ICA), and selecting relevant time ranges.

4. Feature extraction:

In **[1]**

The EEG data is segmented into 10-second intervals, and 1-second segments for each brainwave frequency (alpha, beta, theta, delta) are extracted using Fourier transform. For each frequency band, mean power and mean frequency are computed as features. These features, derived from eight channels (Fp1, Fp2, F3, F4, C3, C4, P3, P4), are used as input for a Long Short-Term Memory (LSTM) deep learning model to classify brainwaves.

In **[2]** instead of selecting the electrodes,  
They captured eight features that are essentially statistical, fractal, and temporal properties of the EEG signal. By examining aspects like variability, frequency power, fractal irregularity, and temporal dynamics, these features enhance the classifier’s ability to distinguish cognitive states based on EEG data

* Variance:Calculated using a 500 ms window with a 492 ms overlap, capturing signal variability.
* Band Power: Extracted from alpha and beta frequency bands to evaluate brainwave activity.
* Minimum Energy: Estimates signal-to-noise ratio by determining the least energy required for signal representation.
* Time Sequence Complexity (TSC): Measures the complexity and dynamic nature of EEG signal sequences.
* Roughness of Fractal Dimension (RFD): Uses Higuchi’s algorithm to quantify the fractal and irregular properties of the signal.
* Hjorth Parameters:
* Activity: Represents the mean power (variance) of the signal.
* Mobility: Measures the rate of change in signal frequency.
* Complexity: Quantifies deviations from simple sine waves in frequency changes.
* Barlow Parameters:
* Mean Amplitude (MA): Captures the average amplitude of the signal.
* Mean Frequency (MF): Represents the average frequency across the signal.
* Spectral Purity Index (SPI): Measures the signal’s irregularity, with a maximum value of one.
* Adaptive Autoregressive (AAR) Parameters:Models variations in EEG signals over time using a recursive least-squares algorithm, generating a 6th-order feature vector.

In **[3]**

They used a neural network model that uses EEG data as input and leverages graph convolution layers to capture spatial relationships between channels. The self-attentive layer focuses on the most significant temporal features, and the fully connected layer refines the features for classification via Softmax. The combination of graph-based spatial analysis and attention-based feature prioritization makes this model highly effective for EEG classification tasks.

* Input Layer:
* Two inputs: EEG signal data (64×640) and correlation coefficient matrix (64×64).
* Forms a graph structure with EEG channels as vertices and their correlations as edges.
* Graph Convolution Layers:
* Two graph convolutional layers:
  + First layer: reduces data dimension to 64×320.
  + Second layer: reduces data dimension to 64×160.
* ReLU activation applied to reduce dependency between layers and avoid overfitting.
* Self-Attentive Layer:
* Extracted features are divided into time slices.
* Attention weights assigned to prioritize important time periods.
* Results in a weighted sum update of time slice information.
* Fully Connected Layer:
* Further integrates features and maps them to hidden space.
* Features are ordered temporally and sent to Softmax for classification.
* Output Layer: Executes the final classification and outputs the recognized categories.

In **[4]**

They implemented a classifier using recurrent convolutional neural networks (RCNN) because properties of this classifier type allow to automatically extract features in the original dataset, as well as to use the previous state of the network to calculate the current state, which allows to identify more patterns in the training set.

RCNNs in EEG data processing:

* Input Layer: 64 EEG channels × 640 time points
* Recurrent Convolutional Layer (RCL): Convolution Kernel Size: 1 × 3. The layer unfolds into a feedforward subnetwork of depth T+1 , where T is the number of time steps.
* Max Pooling Layer: Kernel Size: 1 × 2 - Reduces the dimension of feature maps.
* Fully Connected Layers: - Hidden Layers: Use Rectified Linear Unit (ReLU) activation function.
* Output Layer: Neurons: 6 (one for each category of hand movement)
  + Activation Function: Softmax
* Classification Error Function: Cross Entropy

In **[5]**

This paper combines EEG source imaging with convolution neural networks to optimize the classification problem.Date is projected in scalp EEG data is projected onto the cerebral cortex. Regions of Interest (ROIs) are selected from the motor cortex based on their sensitivity to motor imagination tasks.

* **Feature Extraction**:
  + **ROI Analysis**: Four ROIs with the highest discrimination for motor imagination (MI) tasks are chosen.
  + **Time-Series Extraction**: Extract time series data from brain point sources within the selected ROIs.
  + **Time-Frequency Analysis**: Use Morlet wavelet pairs to perform time-frequency analysis.

Unlike traditional methods that focus only on time and frequency information, this approach incorporates spatial information from the source domain, enhancing the richness of the features extracted.

**Ref:**

[1] A. S. Chakkamallisery, S. T. Pelmo, T. Angsuwatanakul, Y. Pititheeraphab, T. Puttasakul and T. Khemanuwong, "Mind to Motion: EEG-Based Classification of Motor Imagery and Actual Hand Movements Using LSTM Models," 2023 15th Biomedical Engineering International Conference (BMEiCON), Tokyo, Japan, 2023, pp. 1-5, doi: 10.1109/BMEiCON60347.2023.10322025.

[2] Y. Narayan, "Hand Motion Identification Based on EEG Signals Classification," 2021 2nd Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2021, pp. 1-7, doi: 10.1109/GCAT52182.2021.9587556.

[3]L. Chen and Y. Niu, "EEG Motion Classification Combining Graph Convolutional Network and Self-attentiion," 2023 International Conference on Intelligent Supercomputing and BioPharma (ISBP), Zhuhai, China, 2023, pp. 38-41, doi: 10.1109/ISBP57705.2023.10061298

[4] E. Popov and S. Fomenkov, "Classification of hand motions in EEG signals using recurrent neural networks," 2016 2nd International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), Chelyabinsk, Russia, 2016, pp. 1-4, doi: 10.1109/ICIEAM.2016.7911620.

[5] L. Zhou, Q. Zhu, B. Wu, Q. Bing and Z. Qian, "Classification of four-class motion imagination tasks based on EEG by combining EEG source imaging with convolution neural networks," 2021 IEEE International Conference on Medical Imaging Physics and Engineering (ICMIPE), Hefei, China, 2021, pp. 1-4, doi: 10.1109/ICMIPE53131.2021.9698943.

**Summary:**

1. Classify motion states using EEG
2. Data collected is EEG data collected when a subject is asked to do an exam in a construction site to walk and mark the things that are violated. The subject will move in the site. Can use a help button to understand about the location. Or use violation mark to mark the answers.
3. Different labels to classify: In motion to do task, Answering the question, Confused and pressed “I'm stuck”.

**Todo:**

1. Download the EEG data and start the preprocessing with Xiaoting guidance
2. Finalize 2 or 3 feature extraction methodology and try them out