# EEG signal analysis for animated and natural scenes

## Mid-Semester Evaluation Report for B .Tech. Project

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# Introduction

This report will analyze EEG signals to identify the differences in responses of the human brain to natural and animated stimuli. Using advanced spectral decomposition methods like Fourier Bessel Series Expansion (FBSE), the study aims to extract discriminative features reflecting subtle cognitive and perceptual brain dynamics. This study uses signal processing techniques and machine learning to implement classifiers for real-time decoding of brain activity modulated by type of visual content. This type of analysis can be useful in cognitive neuroscience, neuromarketing, and brain-computer interfaces.

## Motivation

Learning how our brains process different visual stimuli, especially natural and animated, is important for advancing neurotechnology devices such as computer interfaces that adapt to dynamic images. Conventional EEG analysis techniques do not frequently detect nuanced spectral features that correlate with diverse categories of visual content. By exploiting FBSE, we can precisely characterize the EEG signals in terms of 'frequency' and 'time'. Thus, it will improve the accuracy of classification and can support real-world applications (attention, visual quality, affective computing).

## Theme of Work

The main idea of this research combines Fourier Bessel spectral analysis and machine learning classifiers for the analysis of EEG signals induced by natural and animated visual stimuli. The paper focuses on enhancing the distinction of stimulus animacy and its cognitive states by bringing in informative features from raw EEG signals via FBSE. The techniques are shown to be valid through extensive experiments, which reveals that their performance is better than that of standard spectral or image-based metrics. This hints at new re strategies that can be used in EEG-driven perceptual and cognitive assessments.

# Literature Review

**2.1 Understanding EEG Signal Processing:** Subha et al. [1] conducted a comprehensive survey that highlighted the challenges posed by the nonlinear and nonstationary characteristics of EEG data, necessitating sophisticated signal processing methods to unveil clinically relevant features. Building on this foundation, Li Hu and Zhiguo Zhang systematically explored the fundamentals of EEG measurement and processing, emphasizing the importance of advanced filtering, feature extraction and noise reduction techniques to enhance the signal quality for accurate interpretation. Together, these works weave a story of evolving methodologies aimed at conquering the innate complexities of EEG signals to enable deeper insights into brain dynamics.

**2.2 Removal of Artifacts(based on EOG & EMG)** Artifact removal from EEG signals is critical because ocular (EOG) and muscle (EMG) artifacts significantly overlap with neural activity, often distorting the true brain signals and complicating interpretation. Advanced automated algorithms such as ICA, MEMD-CCA, IVA, and Riemannian geometry methods have been developed to isolate and suppress these physiological contaminants, preserving authentic EEG for accurate analysis.

2.2.1 Gang Wang et al [2] applied an Independent Component Analysis (ICA) and Multivariate Empirical Mode Decomposition (MEMD) based approach, to remove EOG artifacts (EOAs) from multichannel EEG signals. The EEG signals were decomposed by the MEMD into multiple Multivariate Intrinsic Mode Functions (MIMFs). The EOG-related components were then extracted by reconstructing the MIMFs corresponding to EOAs. After performing the ICA of EOG-related signals, the EOG-linked independent components (ICs) were distinguished and rejected. Finally, the clean EEG signals were reconstructed by implementing the inverse transform of ICA and MEMD.

2.2.3 Corradino and Bucolo[3] developed an automatic preprocessing platform for long-time-scale EEG studies based on ICA and adaptive feedback control. The approach involves multi-stage artifact detection and removal: ICA decomposes EEG into independent components (ICs), which are further analyzed via statistical measures (e.g., kurtosis, spectrum peak) in a feedback loop to identify pulse and periodic artifacts. Detected artifact ICs are cleaned via ordinary least squares regression or frequency domain filtering, and the cleaned EEG is reconstructed from the remaining ICs, reducing the need for manual intervention.

**2.3 Emotion Detection using EEG:** Emotion detection using EEG involves capturing neural signals reflective of different emotional states, then processing these signals with advanced algorithms to classify emotions accurately. Recent advances leverage machine learning and deep learning techniques, including feature extraction from EEG rhythms, domain adaptation and multimodal fusion, significantly improving classification performance and robustness across subjects.

2.3.1 Nalwaya et al[4] present a multivariate variational mode decomposition (MVMD)-based framework, extracting rhythm-specific joint time-frequency features from multichannel EEG to classify four emotions with high accuracy. Their machine learning approach demonstrates over 95% mean detection accuracy, highlighting the strong role of higher-frequency EEG rhythms in emotion recognition.

2.3.2 Nalwaya et al[5] develop an EEG-based emotion identification method using Fourier-Bessel domain adaptive wavelet transform with Lyapunov exponent features and ensemble subspace KNN classification. Tested on a ten-channel EEG database, the technique achieves 96.91% accuracy for four emotion classes, demonstrating high reliability for multisensor nonstationary EEG analysis.

**2.4 EEG and Visual Stimulus:** EEG provides a non-invasive window into brain activity elicited by visual stimuli, capturing dynamic neural responses that vary with stimulus characteristics. Studies demonstrate that distinct EEG patterns, such as event-related potentials and frequency-specific modulations, correlate with different visual features and can be leveraged to decode visual perception and cognition in real-time.

2.4.1 Ajaj et al [6] evaluate the feasibility of using steady-state visually evoked potentials (SSVEP) from EEG to assess perceived image quality in complex natural HD images. Their findings show a significant correlation (0.85) between SSVEP amplitude at the occipital electrode and subjective quality ratings, demonstrating the potential of EEG as an objective measure of image quality perception.

2.4.2 Scholler et al [7] present an EEG-based method to directly measure human perception of video quality changes by detecting the P3 ERP component linked to cognitive processing of quality distortions. Using machine learning on single-trial EEG data, they achieve successful classification of perceived video quality changes, paving the way for neurotechnology-based video quality assessment

# Simulation Results

## Introduction

This section shows the outcomes of simulation, based on classification analyses aimed at developing a robust and competent models. Initially, existing image quality assesment metrics, which include: Perception-based Image Quality Evaluator (PIQE), Naturalness Image Quality Evaluator (NIQE), and Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) were computed. These scores were attached to the images as features to assess classification accuracies between natural and animated scenes.
However, as this preliminary analysis only yeilded moderate accuracy results, a more advanced EEG based method was adapted taking advantage of Fourier Bessel Series Expansion (FBSE) study.

The following summary highlights a comparative sudy of performances.

## Summary

The following table displays the classification accuracies achieved by a variety of models with PIQE, NIQE, BRISQE scores as feature vectors. There is also a combined feature set which includes all three scores.

| Performance Results | | | | |
|---|---|---|---|---|
| Classification Model | PIQE | NIQE | BRISQUE | Combined |
| Fine Tree | 80% | 45% | 60% | 65% |
| Coarse Tree | 80% | 45% | 60% | 65% |
| Fine KNN | 70% | 30% | 45% | 65% |
| Coarse KNN | 50% | 50% | 50% | 50% |

The Fourier Bessel Series Expansion is an analysis framework to study the nature of non-stationary signals using Bessel functions as basis functions. This method is used to represent the EEG signals.

FBSE coefficients $a_k$ for a given signal segment $x(t)$ are computed using the following formula:

$$a_k = \frac{2}{a^2 J_1^2(\xi_k)} \int_0^a x(t) J_0\left(\xi_k \frac{t}{a}\right) dt$$

where:

- $J_0$ is the zeroth-order Bessel function of the first kind,
- $\xi_k$ are the k-th roots of $J_0$,
- $a$ is the total duration (length) of the signal,
- $J_1$ is the first-order Bessel function of the first kind.

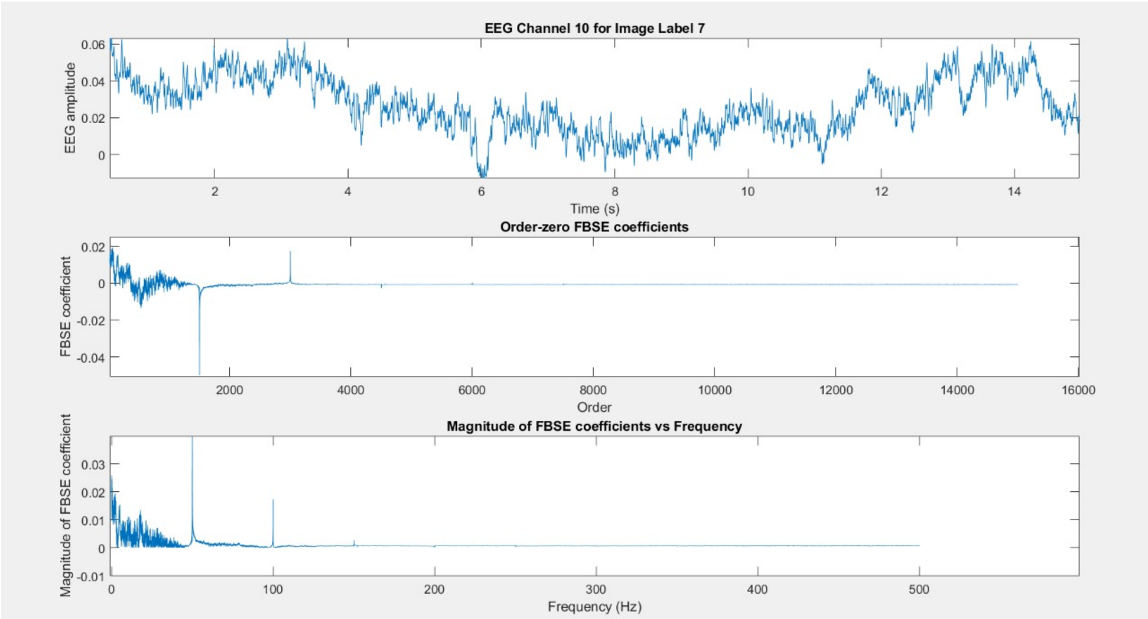


Figure 1: FBSE coefficients extraction

The derived FBSE coefficients describe how the signal projects onto the Bessel functions which are orthogonal in nature. These coefficients account for features, and are labeled as 0 and 1 for natural and animated images respectively, for a supervised classification. The improved accuracy is now 90%.

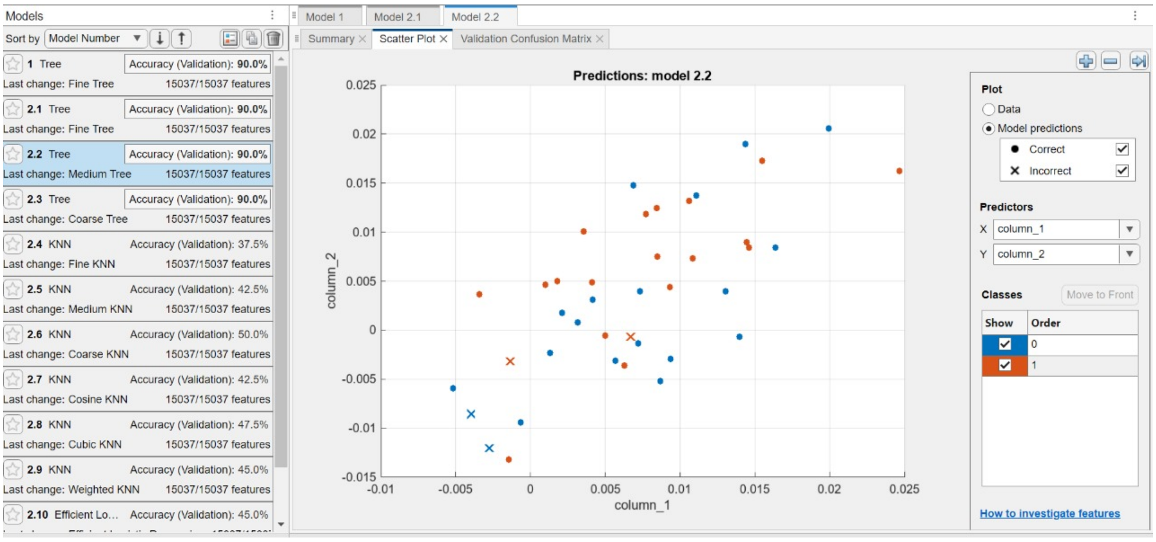


Figure 2: Performance accuracy of classification using FBSE coefficients as features

The enhanced performance is attributed to both the advanced feature extraction as well as the selection of appropriate models. Traditional metrics like NIQE, PIQE, BRISQUE highlighted only limited visual stimulus properties. In contrast, FBSE based extraction provided for better capturing of subject's neural responses to image categories. Tree-based classification models succeeded with higher and discriminative FBSE features.

# Hardware Setup

## BIOPAC MP150 System

We have utilised the BIOPAC MP150 system in order to acquire EEG signal recordings. This system is wirdely popular and used in neuroscience research. The system allows for multi-channel acquisition, from each of the ten electrode points on the human head. Each channel is paired with a special amplifier module called EEG100C which serve the purpose of amplifying the MicroVolts of brain-electrical signals to MilliVolts for proper observation and they also filter out low amplitude signals. Recorded signals are properly analysed and observed using a dedicated software called AcqKnowledge.

Figure 3: BIOPAC MP150 system setup


Figure 4: Cedrus StimTracker device

### Cedrus StimTracker

The Cedrus StimTracker provides for an event tracking system that gives accurate event triggers (such as a high pulse whenever an image is displayed and a low pulse whenever there is a break/blank screen) during the recording experiment. These event markers would be visible in AcqKnowledge which communicates with the StimTracker as well. It can recieve input from a variety of sources like TTL signals, light sensors, audio signals; but we have utilised the option of digital high and low signals, in order to track signal recordings during subject's response to the shown images.

### EEG cap and EL-Check machine

The EEG electrode cap is a flexible piece of headset with electrodes embedded in positions according to the standard 10/20 international system. It is placed on the subjects' head to acquire brain signals through said electrodes.
The EL-Check machine is used for the purpose an impedance check (or an impedance match). It measures the electrode-to-skin impedance on the subjects' head and ensures it remains at a safe value of below 50 Kilo-Ohms. This ensures signal fidelity and minimal noise to bar out incorrect readings.


Figure 5: EL Check (impedance checker) device.

Figure 6: EEG Electrode Cap.

# Planned Workflow and Timeline

We are augmenting our EEG experiment dataset by increasing the number of natural and animated images to 100 each, thereby expanding the overall test duration. To keep the session length balanced, the time spent on one image will be shortened, resulting in the possibility of collecting a greater number of EEG samples which are also statistically significant. After acquiring this data, we will start working with Fourier Bessel Series Expansion on the new extended data. This method is designed to improve the ability to extract features, and classify things, while providing insight into how the brain reacts to a number of different visual stimuli.

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