GVS-EEG Project

Phase I

Report

Beta Burst Analysis of EEG in PD and HC Cases Under Different Medication and GVS Conditions

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1 | Description of the project:

- **Brief Explanation:**

Parkinson's Disease is a prevalent issue impacting millions as they grow older. The long-term objective of this research is to discover a new treatment for this condition. At the Pacific Parkinson's Research Center within DMCBH at UBC, we are exploring the use of Galvanic Vestibular Stimulation (GVS) as a non-invasive brain stimulation technique, given the promising evidence that GVS positively influences behavioral metrics.

This report outlines the methods and findings from the initial phase of my assigned project, which involves a comprehensive analysis of Beta Bursts across various cases and conditions.

- **Data Description:**

In this phase of the project, we recorded preprocessed EEG data from various subjects. The analysis focused on resting EEG data from 22 Healthy Controls (HC) and 20 Parkinson's Disease (PD) patients. For the PD patients, data were collected under two conditions: OFF Medication, where patients chose not to take their medication, and ON Medication, during which they had taken their medication. Additionally, we gathered two types of data for both PD and HC cases, depending on whether Galvanic Vestibular Stimulation (GVS) was applied. The data were collected from 27 electrodes (channels) at a sampling frequency of 500 Hz, comprising 60 trials, with each trial lasting 1000 milliseconds.

As previously stated, the aim of this phase of the project is to analyze Beta Bursts. Consequently, the study concentrates on three key electrodes: **C3, Cz, and C4**. These selected electrodes are more effective in representing the motor functions of the subjects. This choice aligns with the project's objective of identifying an appropriate solution for patients with Parkinson's Disease.

2 | Extracted Features:

In this study, 10 features have been extracted from recorded EEG signals from patients to be compared and analyzed accordingly.

Following points should be taken into consideration before delving into the features' description:

- A Sample is the recorded rest EEG from a subject in one trial with the sampling frequency of 500 Hz and duration of 1000 Miliseconds.
- A Burst is defined as parts of the signal that exceeds the elicited threshold. The threshold for each sample is elicited individually based on the Mean and Standard Deviation of that Sample.
- All features have been extracted individually for three different channels mentioned earlier.
- For a dataset, the value of features represents the Mean value elicited from all subjects and all trials.

1. **Total Burst Number (TBN):**
   This feature indicates number of bursts in a sample.

2. **Total Burst Time (TBT):**
   This feature indicates the cumulative time of bursts in a sample. Higher TBT means that more portion of the signal is labeled as a burst.

3. **Average Burst Time (ABT):**
   This feature indicates the average time of each burst in a sample. Although there might be longer and shorter bursts in a sample, this feature represents the average time of bursts in a sample.

4. **Maximum Burst Time (MBT):**
   This feature indicates the longest burst duration in a sample. Long bursts could be a leading signature in a recorded EEG signal.

5. **Average Burst Amplitude (ABA):**
   This feature indicates the mean amplitude of bursts in a sample.

6. **Maximum Burst Amplitude (MBA):**
   This feature indicates maximum amplitude of the burst in a sample. It's assumed that there is a considerable difference between the amplitude of different datasets.

7. **Average Burst Occurrence Time (ABOT):**
   This feature indicates the average time (a number from 0 to 1000) that bursts occur in a sample. Specifically, the goal of extracting this feature is to understand that in which time interval bursts are more likely to show up.

8. **Maximum Burst Occurrence Time (MBOT):**
   This feature indicates the time (a number from 0 to 1000) that the burst with Highest Amplitude occurs.

9. **Average Burst Energy (ABE):**
   This feature indicates the mean of energy of bursts, elicited by finding the energy of each burst and finding the mean of it in a sample.

10. **Maximum Burst Energy (MBE):**
    This feature indicates the maximum energy that a burst has in a sample. It could belong to the burst with highest amplitude, longest duration, or any other bursts in the sample.

These features are subsequently utilized to compare the datasets and analyze the data.

3 | MATLAB Script:

Full MATLAB script for this stage of the project, including processing of the signal, feature extraction, and plotting results can be accessed on my GitHub repository via following link:

My GitHub Repository for GVS-EEG Project

However, the following is the MATLAB script used to process the data and extract required features:

```
%% Defining Required Functions for Beta Burst Analysis of C3, Cz, C4

% Extracting Channels from Data
function [Signal_C3, Signal_Cz, Signal_C4] = Channel_Extracter(Data)
Signal_C3 = transpose(Data(:,12));
Signal_Cz = transpose(Data(:,13));
Signal_C4 = transpose(Data(:,14));
end

% Filtering Beta Oscillations
function [Filtered_Signal_C3, Filtered_Signal_Cz, Filtered_Signal_C4] = Filter_Applier(Signal_C3, Signal_Cz, Signal_C4)
% Defining Sampling Frequency
fs = 500;

% New Modified Bandpass Filter
BPFilter = fir1(100,[13, 30]/(fs/2), "bandpass");

Filtered_Signal_C3 = filter(BPFilter, 1, Signal_C3);
Filtered_Signal_Cz = filter(BPFilter, 1, Signal_Cz);
Filtered_Signal_C4 = filter(BPFilter, 1, Signal_C4);

end

% Finding Suitable Threshold
function [Threshold_C3, Threshold_Cz, Threshold_C4] = Threshold_Finder(filtered_Signal_C3, filtered_Signal_Cz, filtered_Signal_C4)
Mean_C3 = sum(filtered_Signal_C3)/length(filtered_Signal_C3);
Mean_Cz = sum(filtered_Signal_Cz)/length(filtered_Signal_Cz);
Mean_C4 = sum(filtered_Signal_C4)/length(filtered_Signal_C4);

STD_C3 = std(filtered_Signal_C3);
STD_Cz = std(filtered_Signal_Cz);
STD_C4 = std(filtered_Signal_C4);

Threshold_C3 = Mean_C3 + 1.5 * STD_C3;
Threshold_Cz = Mean_Cz + 1.5 * STD_Cz;
Threshold_C4 = Mean_C4 + 1.5 * STD_C4;
end

% Finding Features of the Signal
function [TBN, TBT, ABT, MBT, ABA, MBA, ABOT, MBOT, ABE, MBE] = Feature_Finder(Filtered_Signal, Threshold)
% Number of Beta Bursts for sample channel C3 + Total Burst Time (msec)
% + Average Burst Time (msec)

Burst_Detector = Filtered_Signal > (Threshold * 1.05);
% Ignoring Negligible Peaks by considering 5 percent of error

burst_starts = find(diff([0, Burst_Detector]) == 1); % Start of bursts
burst_ends = find(diff([Burst_Detector, 0]) == -1); % End of bursts
```

```

% Ensure that starts and ends are matched correctly
if length(burst_starts) > length(burst_ends)
burst_ends(end + 1) = length(Filtered_Signal); % Append last index if needed
end

% Count number of bursts
TBN = length(burst_starts);
TBT = ((sum(burst_ends - burst_starts))/length(Filtered_Signal))*1000;
ABT = TBT / TBN;
MBT = (max(burst_ends - burst_starts) / length(Filtered_Signal))*1000;

% Finding Average Burst Amplitude (ABA) + Maximum Burst Amplitude (MBA)
% + Finding Average Burst Occurrence Time (ABOT)
% + Fidning Maximum Burst Occurrence Time (MBOT)

Burst_Maximums = zeros(1,TBN);
Burst_Occurrences = zeros(1,TBN);

for i = 1:1:TBN
Burst_Maximums(i) = max(Filtered_Signal(1,(burst_starts(i)):(burst_ends(i))));
Burst_Occurrences(i) = find(Filtered_Signal(1,(burst_starts(i)): ...
(burst_ends(i)))==Burst_Maximums(i)) + burst_starts(i) - 1;
end

ABA = sum(Burst_Maximums) / length(Burst_Maximums); % Average Burst Amplitude
MBA = max(Burst_Maximums);
ABOT = ((sum(Burst_Occurrences) / TBN) / length(Filtered_Signal)) * 1000;

[~, Temp2] = max(Burst_Maximums);
MBOT = (Burst_Occurrences(Temp2) / length(Filtered_Signal)) * 1000;

% Finding Burst Energy
Burst_Energies = zeros(1,TBN);
for i = 1:1:TBN
Temp = Filtered_Signal(1,(burst_starts(i)):(burst_ends(i)));
Burst_Energies(i) = sum(Temp.^2);
end
ABE = (sum(Burst_Energies)) / TBN;
MBE = max(Burst_Energies);
end
```

4 | Findings (Feature-Based):

• 1 | Total Burst Number (TBN):

The following figures represent the PDF (Probability Density Function) for six different Datasets:

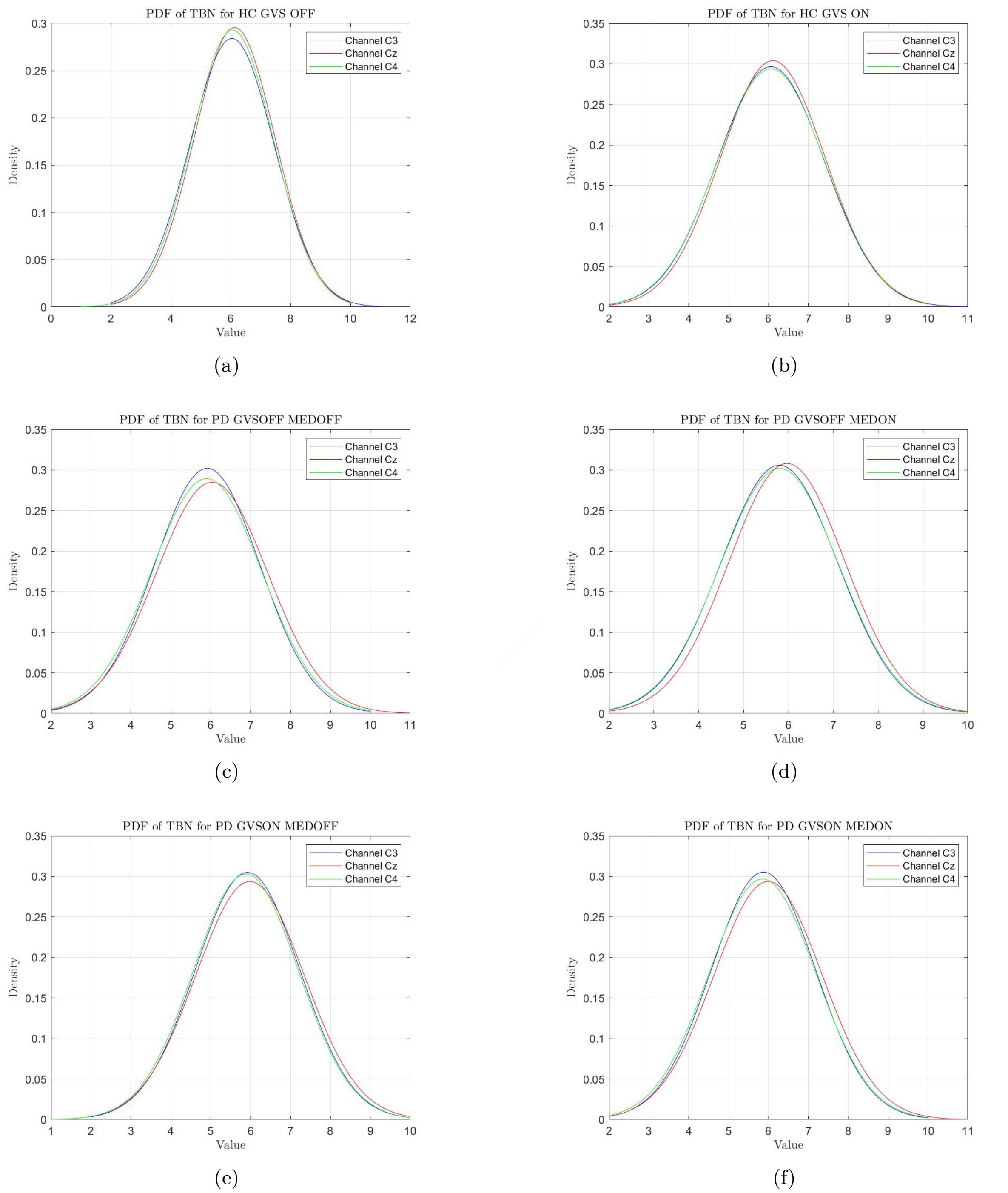
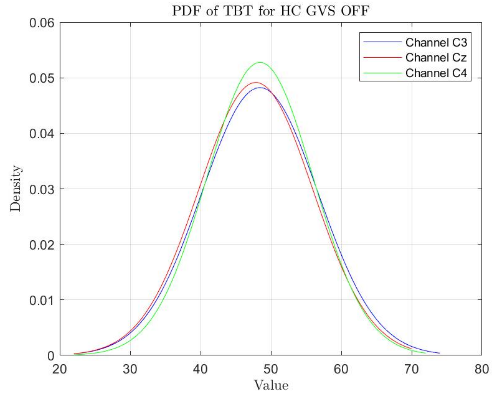


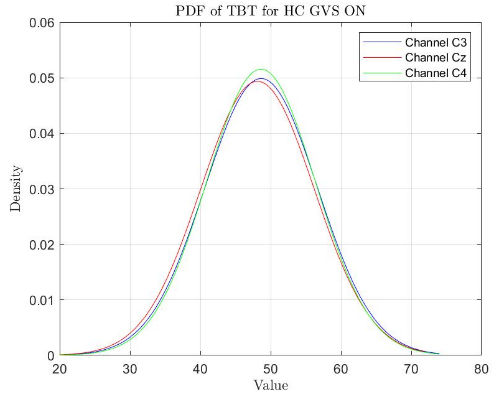
Figure 1: Distribution of TBN Feature across all subjects and trials of a Dataset

• 2 | Total Burst Time (TBT):

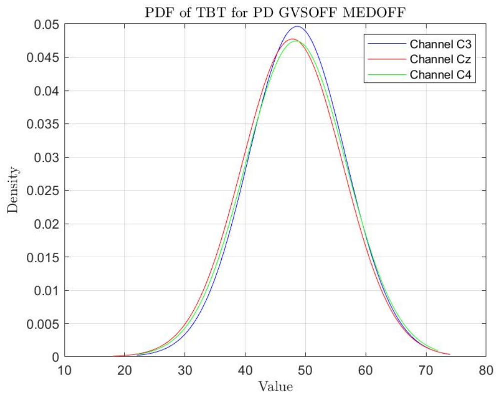
The following figures represent the PDF (Probability Density Function) for six different Datasets:



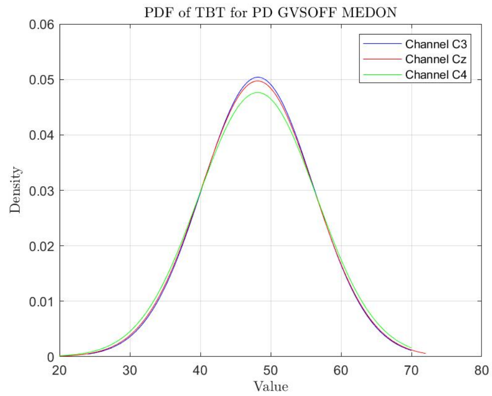
(a)



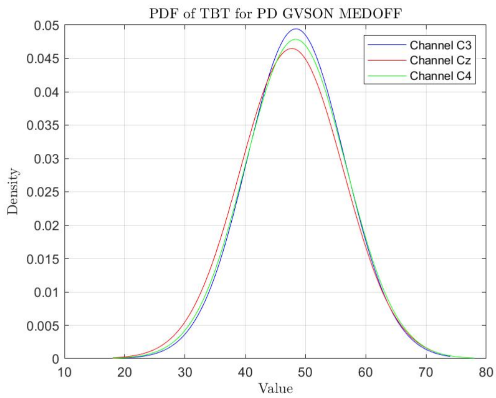
(b)



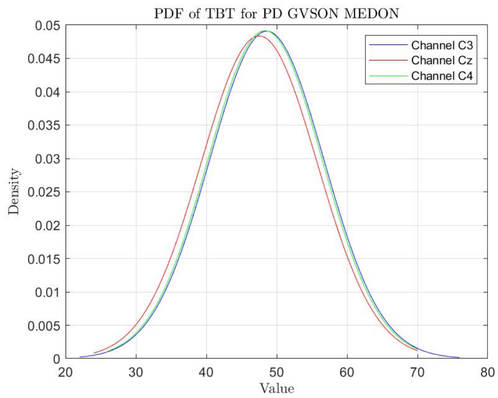
(c)



(d)



(e)

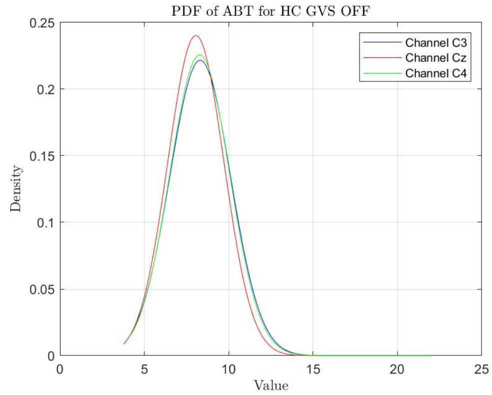


(f)

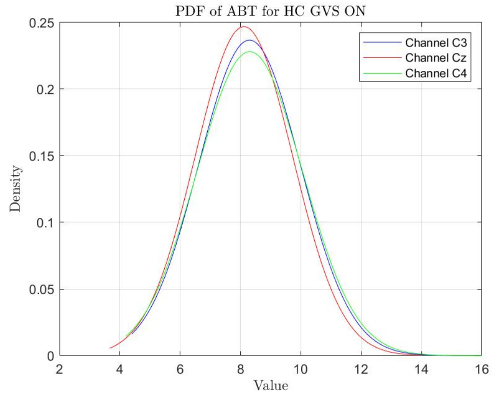
Figure 2: Distribution of TBT Feature across all subjects and trials of a Dataset

• 3 | Average Burst Time (ABT):

The following figures represent the PDF (Probability Density Function) for six different Datasets:



(a)



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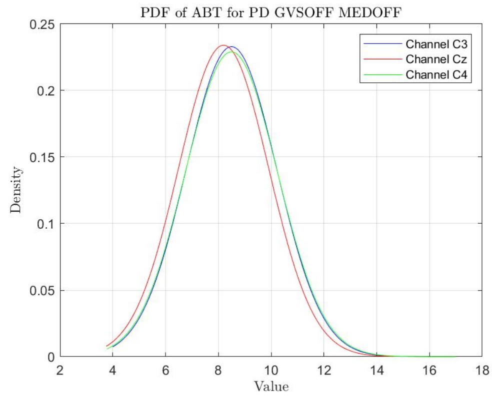

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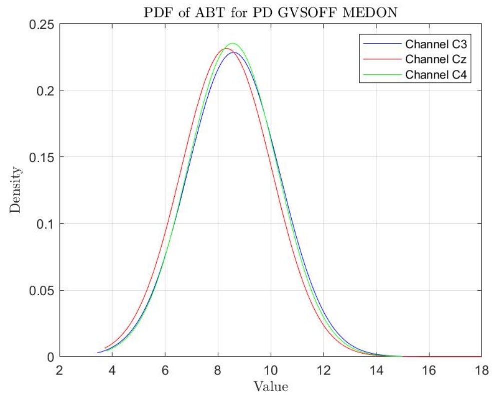

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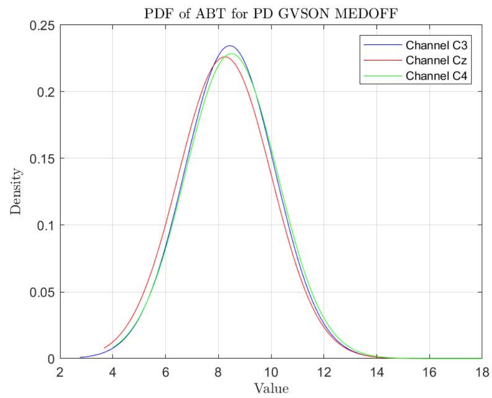

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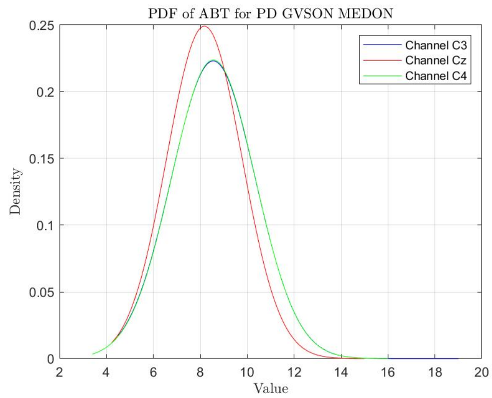


(f)

Figure 3: Distribution of ABT Feature across all subjects and trials of a Dataset

• 4 | Maximum Burst Time (MBT):

The following figures represent the PDF (Probability Density Function) for six different Datasets:

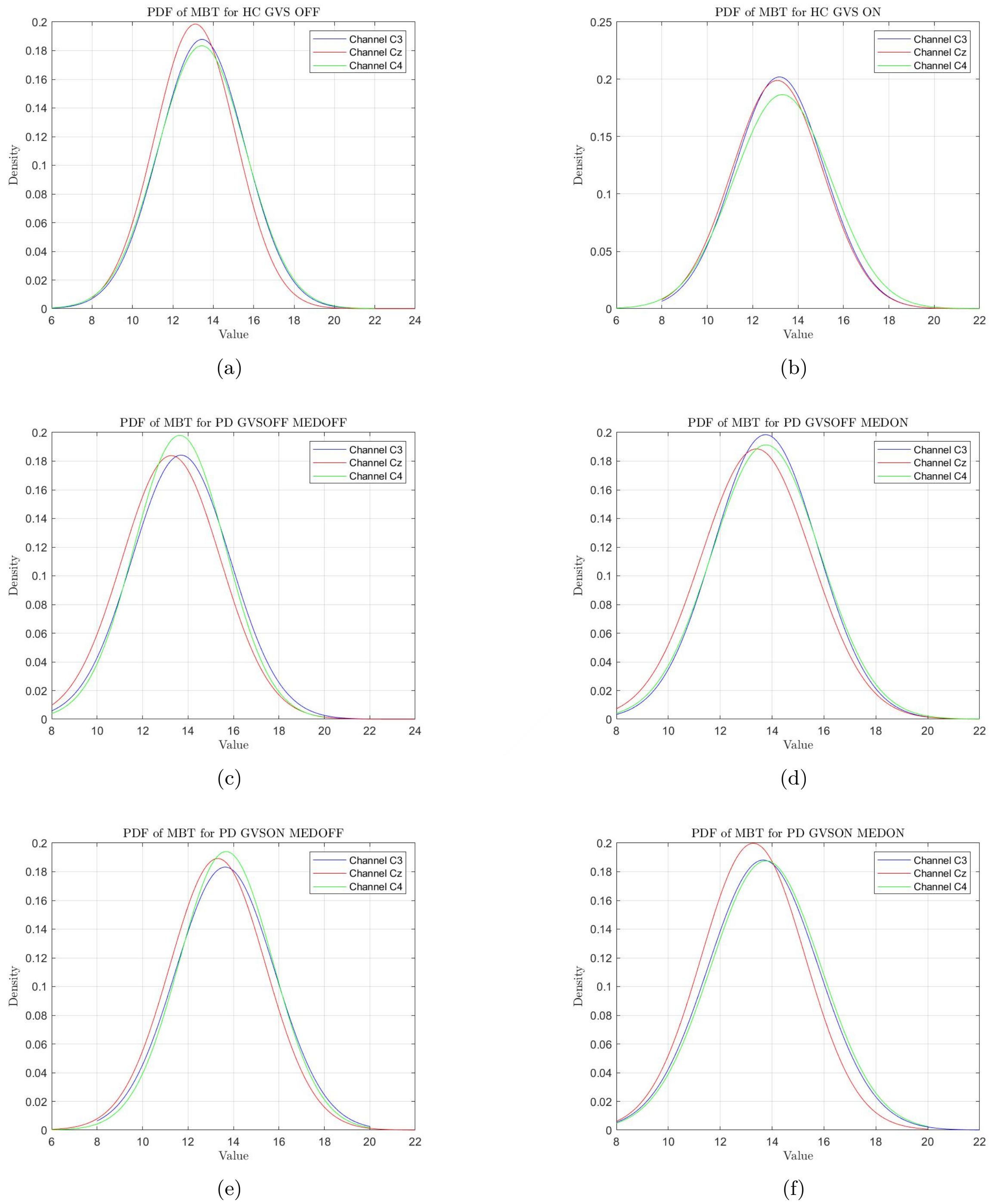
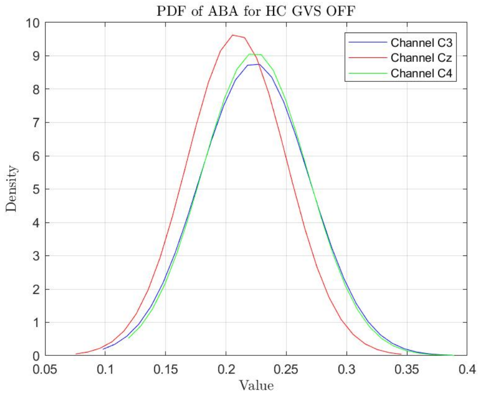


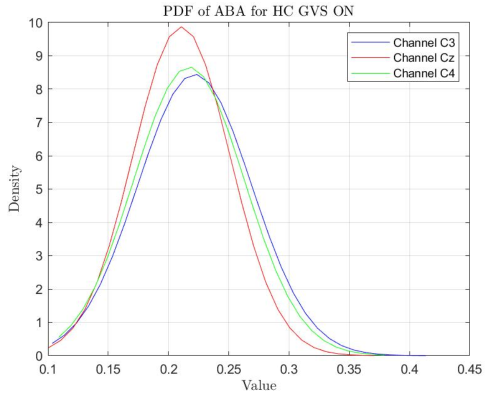
Figure 4: Distribution of MBT Feature across all subjects and trials of a Dataset

• 5 | Average Burst Amplitude (ABA):

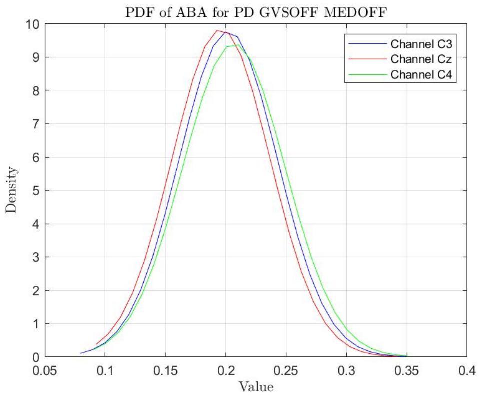
The following figures represent the PDF (Probability Density Function) for six different Datasets:



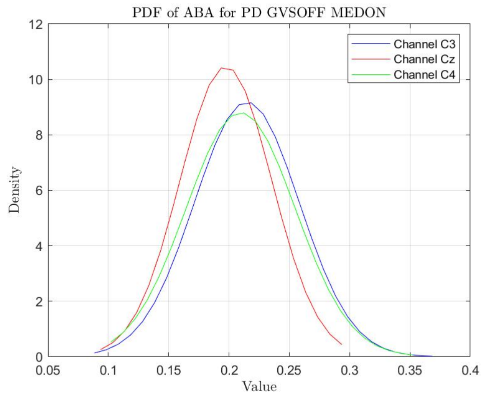
(a)



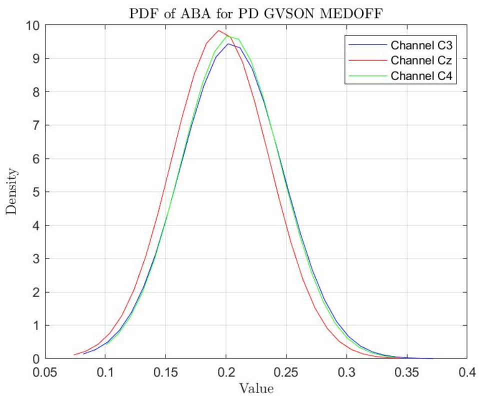
(b)



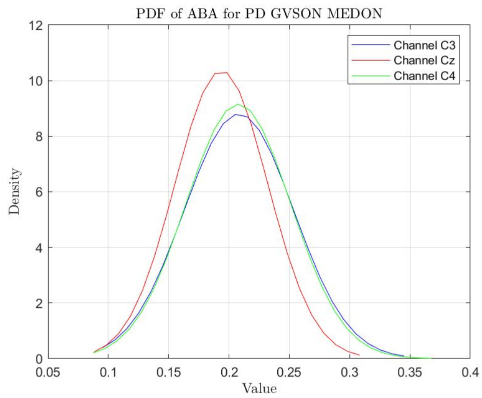
(c)



(d)



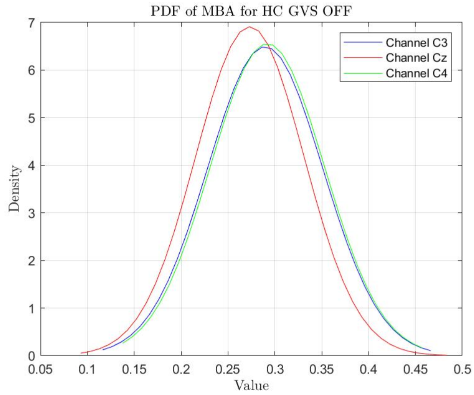
(e)



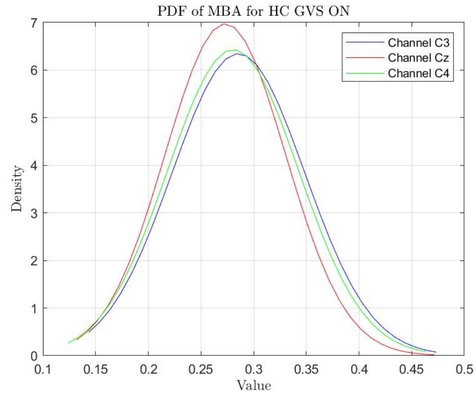
(f)

Figure 5: Distribution of ABA Feature across all subjects and trials of a Dataset

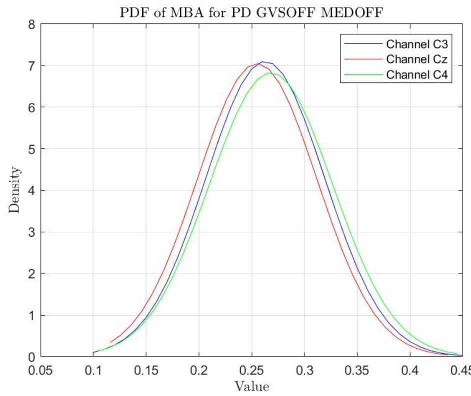
• 6 | Maximum Burst Amplitude (MBA):
The following figures represent the PDF (Probability Density Function) for six different Datasets:



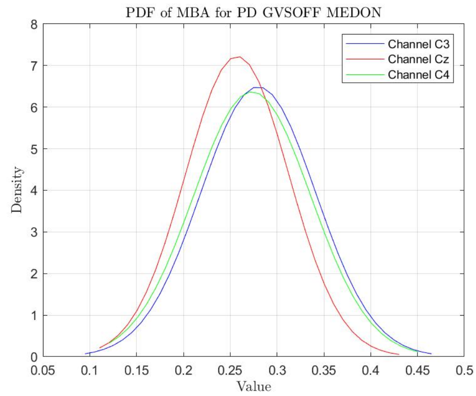
(a)



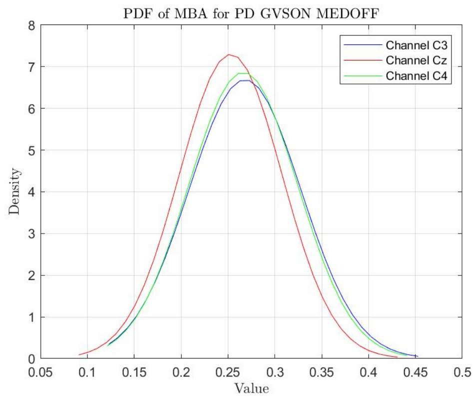
(b)



(c)



(d)



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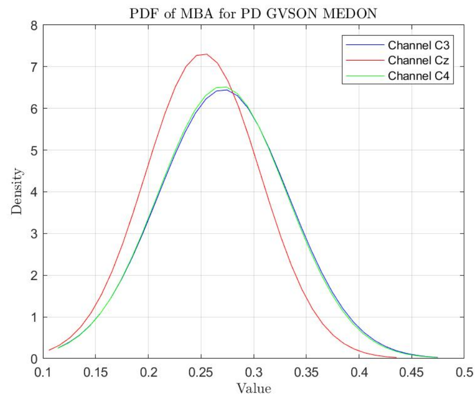
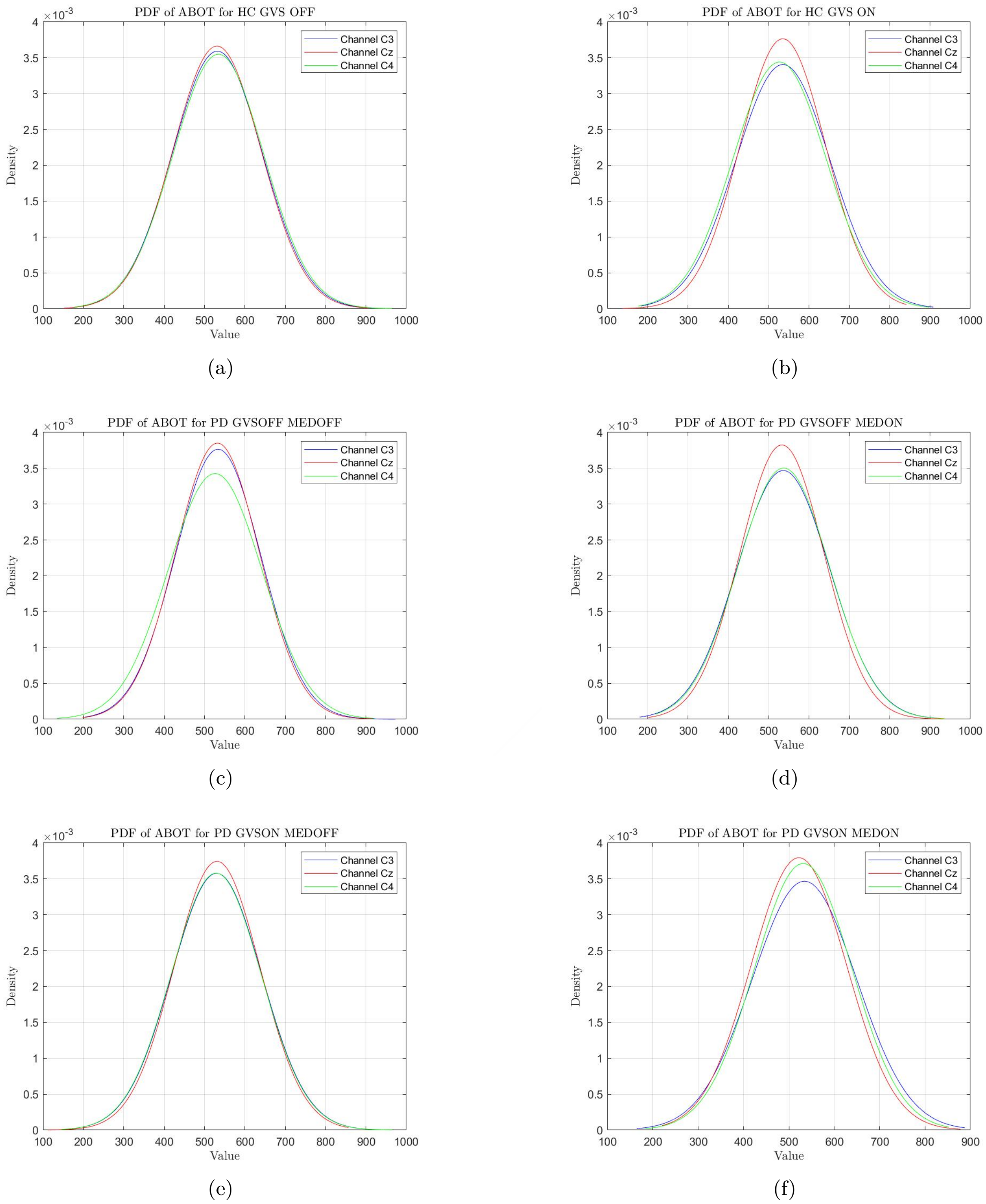


(f)

Figure 6: Distribution of MBA Feature across all subjects and trials of a Dataset

- **7 | Average Burst Occurrence Time (ABOT):**

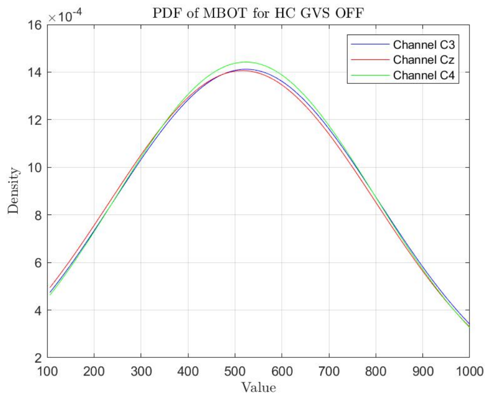
The following figures represent the PDF (Probability Density Function) for six different Datasets:



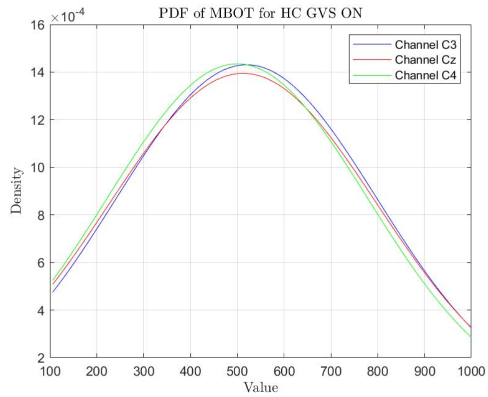
(a) (b) (c) (d) (e) (f)

Figure 7: Distribution of ABOT Feature across all subjects and trials of a Dataset

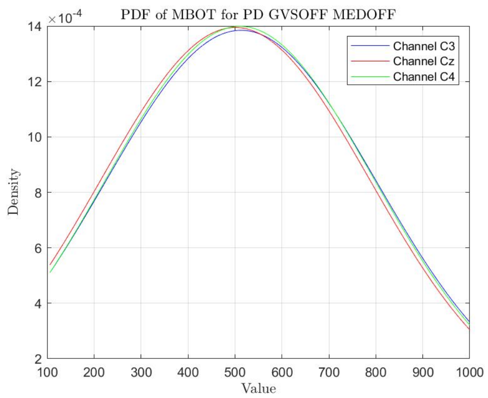
• 8 | Maximum Burst Occurrence Time (MBOT):
The following figures represent the PDF (Probability Density Function) for six different Datasets:



(a)



(b)



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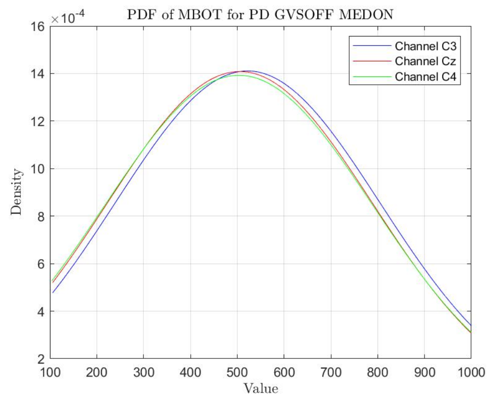

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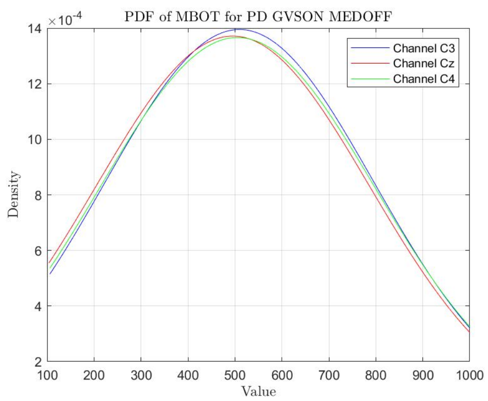

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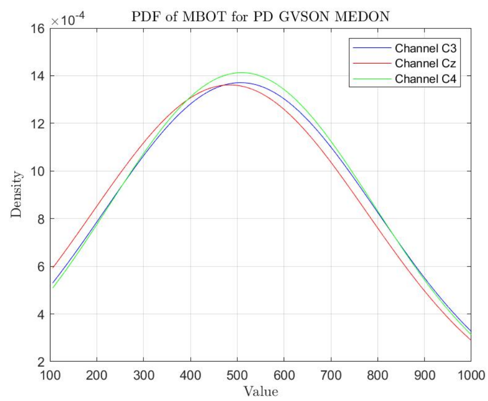
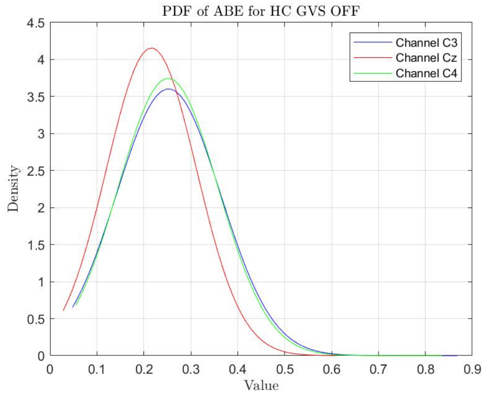


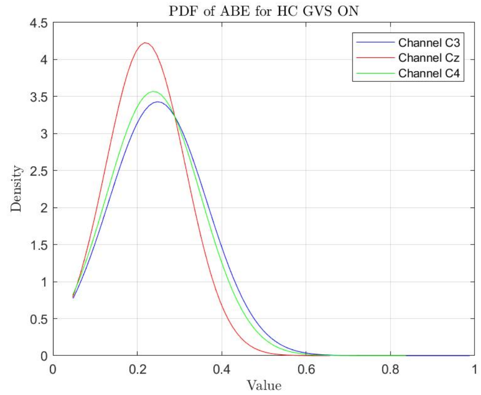
(f)

Figure 8: Distribution of MBOT Feature across all subjects and trials of a Dataset

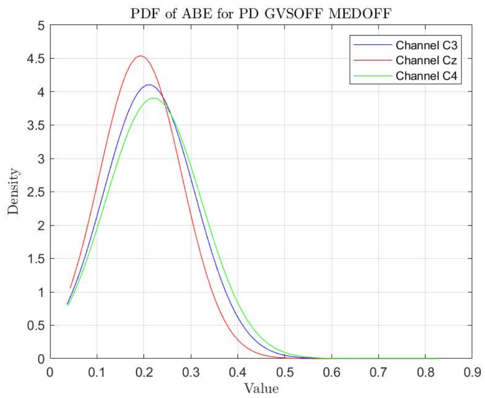
• 9 | Average Burst Energy (ABE):
The following figures represent the PDF (Probability Density Function) for six different Datasets:



(a)



(b)



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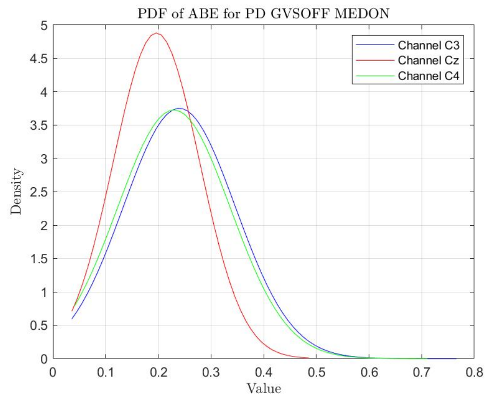
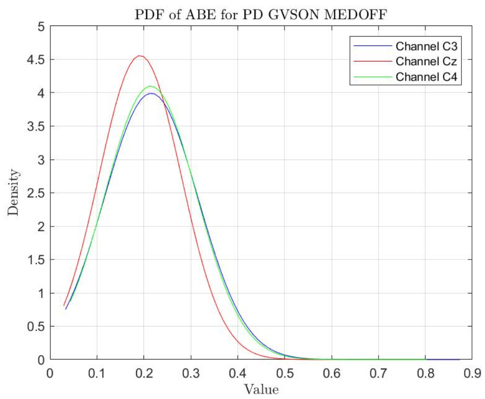


(d)



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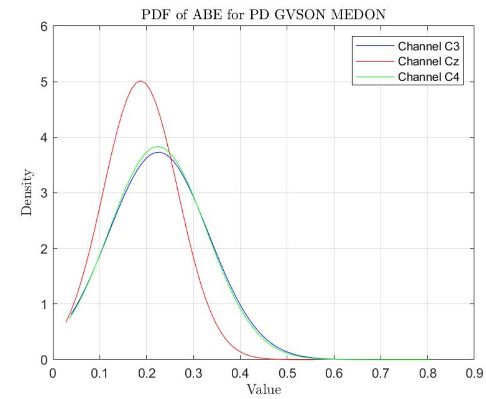


(f)

Figure 9: Distribution of ABE Feature across all subjects and trials of a Dataset

• 10 | Maximum Burst Energy (MBE):

The following figures represent the PDF (Probability Density Function) for six different Datasets:

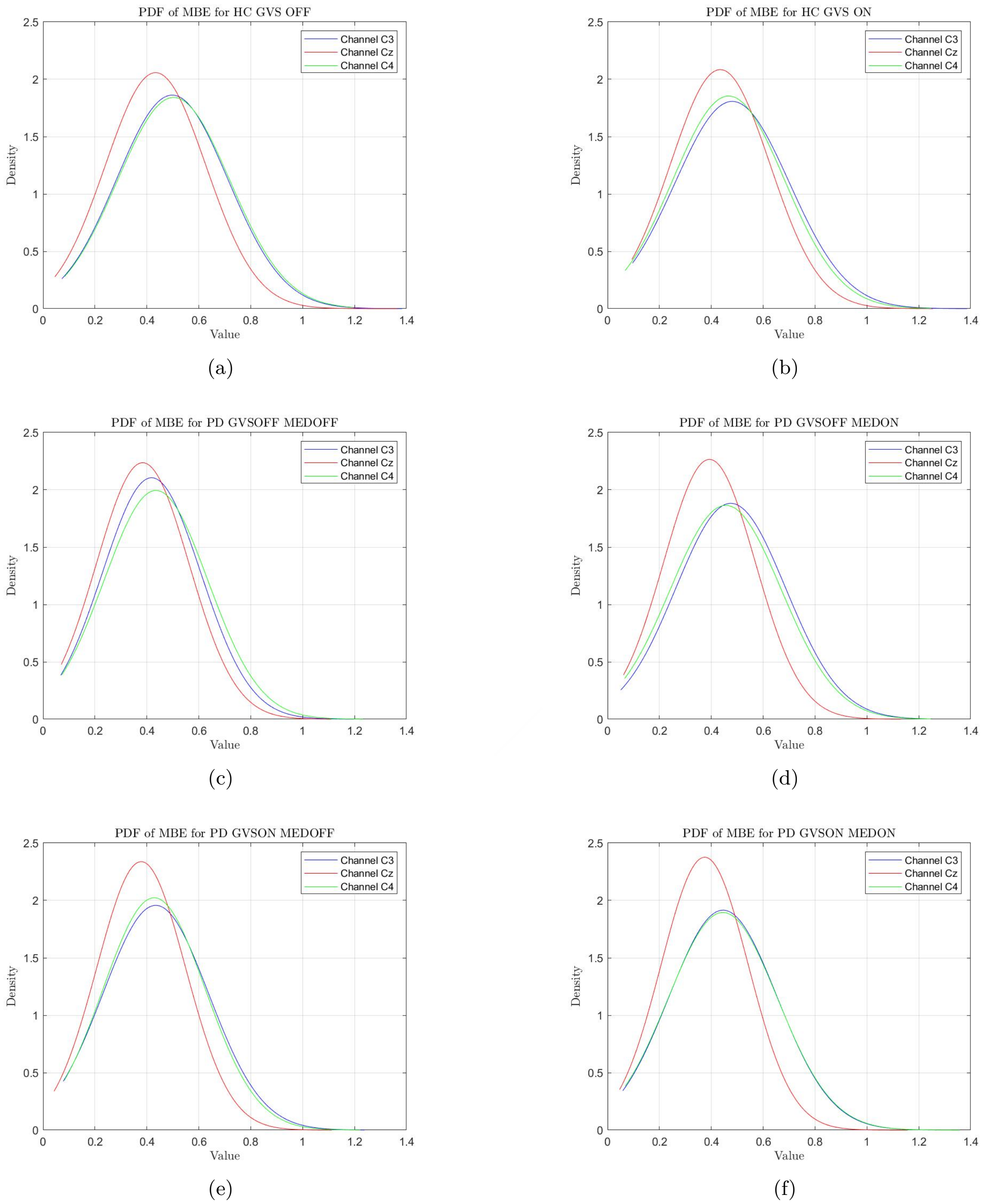
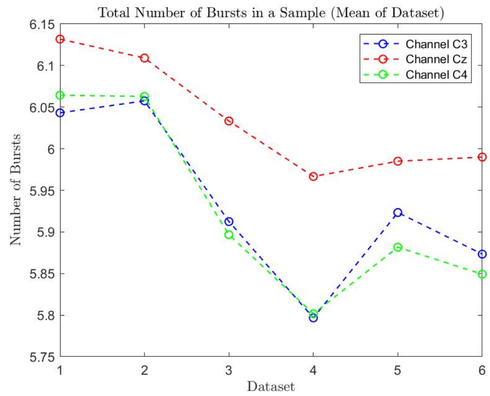


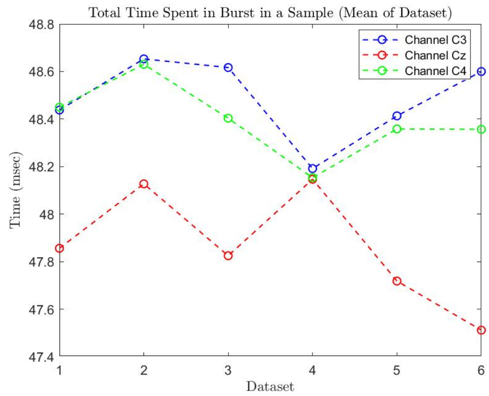
Figure 10: Distribution of MBE Feature across all subjects and trials of a Dataset

5 | Findings (All-in-One):

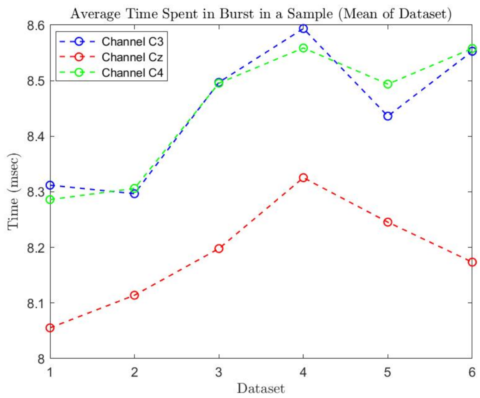
Above findings can help us figure out the properties of each Dataset individually. However, for a better understanding of the differences between available datasets, comprehensive figures are presented below:



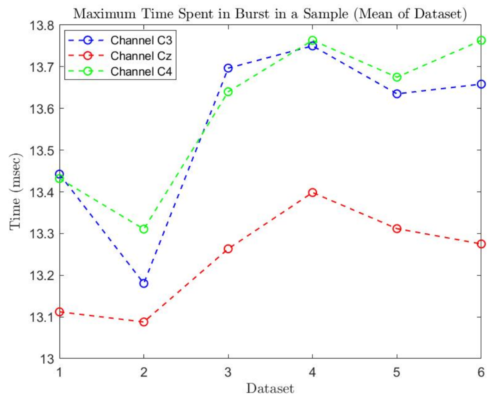
(a) Mean TBN Value



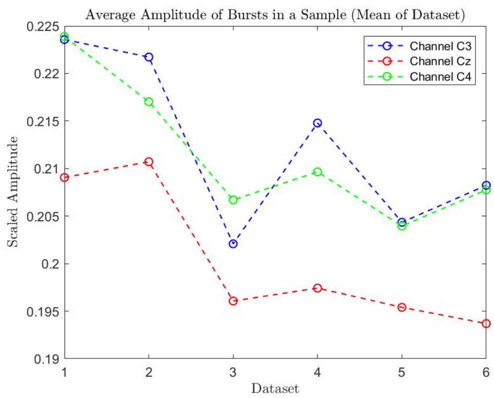
(b) Mean TBT Value



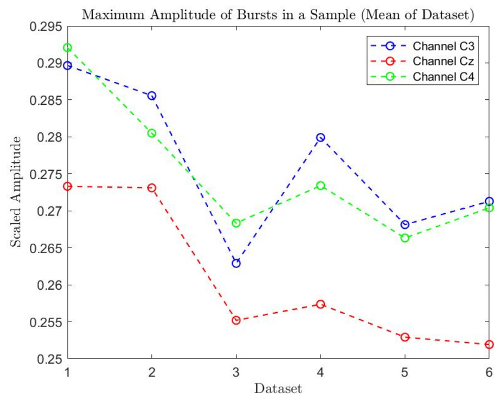
(c) Mean ABT Value



(d) Mean MBT Value

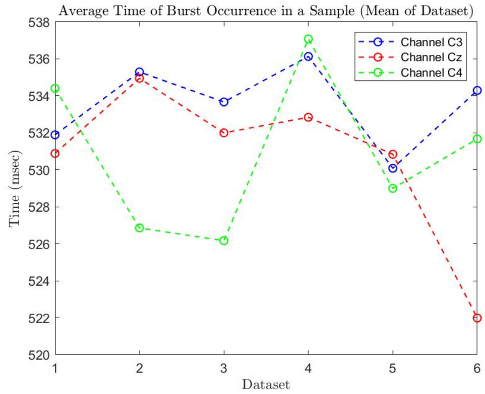


(e) Mean ABA Value

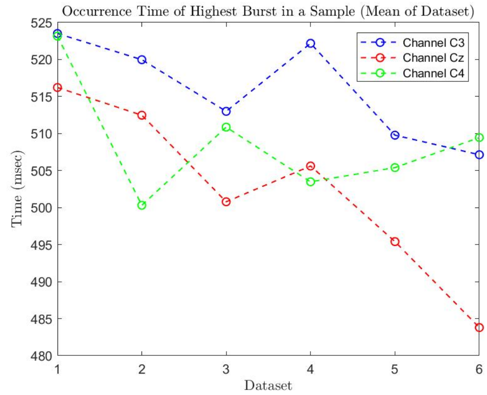


(f) Mean MBA Value

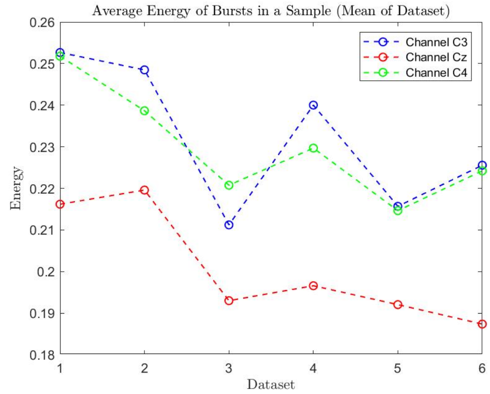
Figure 11: Mean Value of Features for All 6 Datasets and 3 Channels



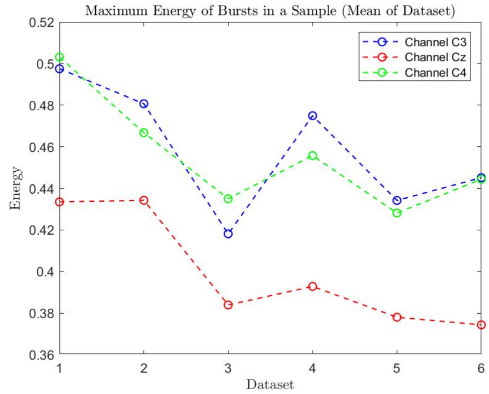
(a) Mean ABOT Value



(b) Mean MBOT Value



(c) Mean ABE Value



(d) Mean MBE Value

Figure 12: Mean Value of Features for All 6 Datasets and 3 Channels

- **Summary of Key Findings:**

  1. Average/Maximum Burst Time in Patients diagnosed with Parkinson's Disease is assumed to be longer according to plots **c,d** in figure **11**. Mentioned Plots also reveal that GVS could positively impact the mentioned features and reduce them, while the effect of medication is not clear.
  2. Amplitude of the bursts is lower in PD cases compared to Healthy Controls. However, effect of GVS or Medication seems to be negligible.
  3. Plots **a,b** from figure **12** implies that Beta Bursts in PD patients that are ON Medication and also affected by GVS relatively occurs sooner compared to the opposite group that are OFF medication and GVS is not applied.
  4. Plots **c,d** from figure **12** shows that Beta Bursts in Healthy Controls have higher Energy Compared to PD Cases.

6 | Conclusion:

The study focused on Beta Burst Analysis across different subject groups, including healthy controls (HC) and Parkinson's disease (PD) patients who were assessed both on and off medication and galvanic vestibular stimulation (GVS). The methodology involved filtering recorded EEG signals and establishing a threshold for burst detection. Ten features were extracted from each resting EEG signal for a comprehensive analysis, which included comparisons across channels (C3, Cz, and C4) and datasets.

Key findings indicate the potential to differentiate between cases and the effects of GVS or medication. However, the number of extracted features was insufficient to draw definitive conclusions regarding the differences between datasets. It is suggested that exploring additional features or focusing on task-based EEG instead of resting EEG may yield more reliable outcomes.