Discussion

This experiment reinforced the importance of precise electrode placement and patient positioning in acquiring high-fidelity ECG signals. The clarity of Lead II underlines its clinical utility for rhythm analysis. Using a digital ECG system allowed real-time observation of the waveforms, aiding in the identification of distinct cardiac events. Although the sensors used did not detect any anomalies, the process highlighted how small variances in waveforms could indicate critical health conditions. Overall, the practical exposure offered deeper understanding of ECG interpretation and its relevance in diagnostic cardiology.

References

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2. G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, May–Jun. 2001. doi: 10.1109/51.932724.
3. PhysioNet, "WFDB Toolbox for MATLAB and Octave," PhysioNet, 2020. [Online]. Available: https://physionet.org/content/wfdb-matlab/

Experimental Observation

Using PhysioNet EEG datasets, we examined signals from locations like Fp1, Fp2, C3, C4, O1, and O2. Each wave type reflected specific mental states: alpha during relaxation and beta during concentration. Data was pre-recorded; no live recordings were conducted.

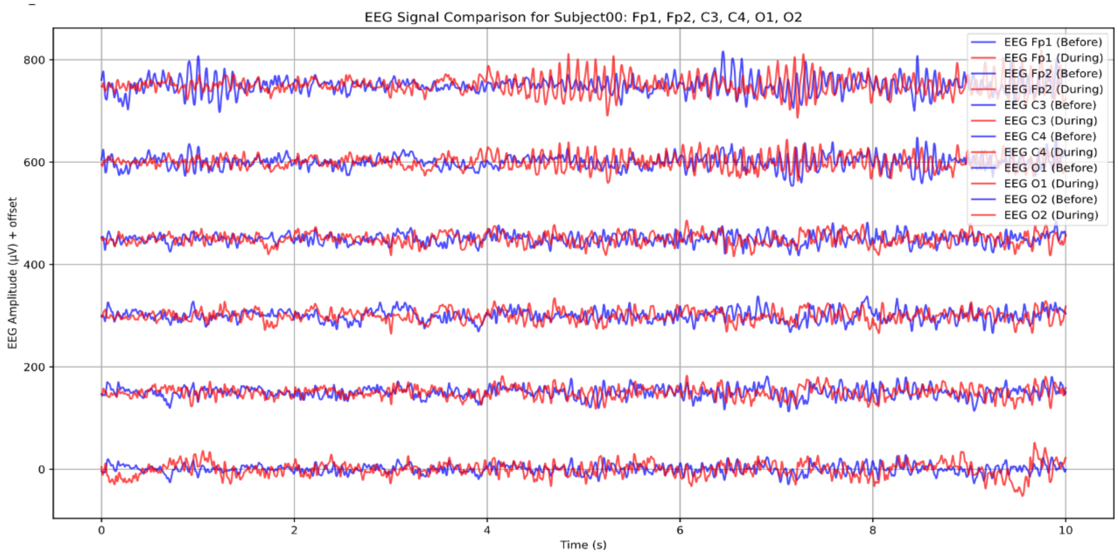

Figure 1: A diagram of EEG signal in different frequencies.

Discussion and Conclusion

Despite not using real-time EEG equipment, the study effectively introduced EEG analysis through authentic datasets. We learned to recognize signal patterns, interpret brainwave frequencies, and understand electrode placements. The experiment clarified how mental states influence EEG signals, reinforcing core concepts of brain activity analysis.

References:

1. N. V. Thakor and Y.-S. Zhu, “Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection,” *IEEE Transactions on Biomedical Engineering*, vol. 38, no. 8, pp. 785–794, Aug. 1991. doi: 10.1109/10.83589.

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3. PhysioNet, “EEG Motor Movement/Imagery Dataset,” PhysioNet, 2019. [Online]. Available: https://physionet.org/content/eegmmidb/1.0.0/

Heaven's light is our guide

RAJSHAHI UNIVERSITY OF ENGINEERING AND TECHNOLOGY

Department Of Electrical & Computer Engineering

Course Title:

Bio Medical Engineering Sessional

Course Code:

ECE 4144

Experiment No. 3

Experiment Name:

Experimental Observation of Various Features of an ECG Signal Collected from PhysioNet Public Dataset

Date of Experiment: **06 August, 2025** **Date of Submission:** **13 August, 2025**

Submitted to:	Submitted by:
Md Mayenul Islam	Syed Mahmudul Imran
Assistant Professor, EEE	Roll:2010058
RUET	ECE 2020-21

Experiment No: 03

Experiment Name: Experimental Observation of Various Features of an ECG Signal Collected from PhysioNet Public Dataset

Objectives:

1. To measure RR, PP, and PR intervals using PhysioNet ECG data.
2. To relate temporal cardiac features to physiological parameters like heart rate.

An ECG records heart's electrical activity via features such as the P wave, QRS complex, and T wave.

- **RR Interval:** Time between successive R peaks; used for heart rate and arrhythmia detection.
- **PP Interval:** Time between P peaks; assesses atrial rhythm.
- **PR Interval:** Time from P wave start to QRS onset; indicates atria-to-ventricle conduction time.

Heart rate (HR) is calculated from the RR interval:

$$\text{HR} = \frac{No. of\ peaks}{Time(s)} \times 60$$

Dataset Description:

MIT-BIH Arrhythmia Database (PhysioNet) — 48 half-hour ECG recordings from 47 subjects (1975–1979).

- **Fs:** 360 Hz, ~110,000 annotations.
- ~60% inpatients, ~40% outpatients.

Record Used:

- 100 (files: .atr, .dat, .hea, .xws).

Tools

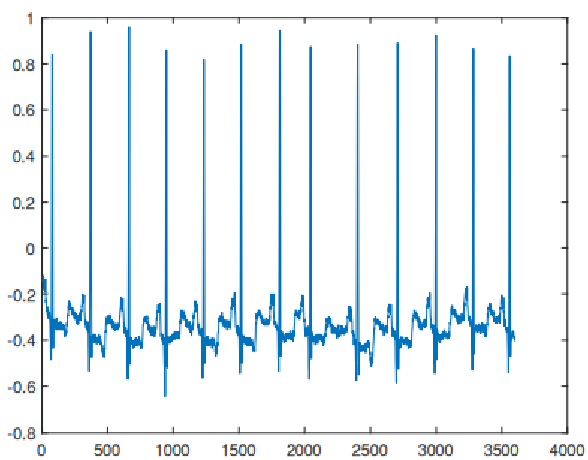
- MATLAB
- WFDB Toolbox for MATLAB

Code:

```
[sig, Fs, tm] = rdsamp('mit bih/100', 1);
plot(sig(1:3600, 1))
time = 10; %in seconds
```

```
no_of_r_peak = 13;
HR = (no_of_r_peak/time)*60;
fprintf('Heart Rate (bpm): %.2f\n', HR);
R_Peak_positions = [78 371 664 948 1232];
rri = diff(R_Peak_positions);
RR_mean = mean(rri);
fprintf('Mean R-R Interval (samples): %.2f\n', RR_mean);
rr_mean_second = RR_mean/360;
fprintf('Mean R-R Interval (seconds): %.4f\n', rr_mean_second);
P_Peak_positions = [311 605 885 1164 1467];
ppi= diff(P_Peak_positions);
PP_mean = mean(ppi);
fprintf('Mean P-P Interval (samples): %.2f\n', PP_mean);
pp_mean_second = PP_mean/360;
fprintf('Mean P-P Interval (seconds): %.4f\n', pp_mean_second);
```

Output:



Heart Rate: 78 bpm
Mean RR Interval: 0.8014 s
Mean PP Interval: 0.8028 s

Result & Discussion

The analysis confirmed accurate extraction of ECG features from PhysioNet data.

- HR of 78 bpm aligns with a normal resting heart rate.
- RR and PP intervals showed consistent atrial and ventricular activity.
  This validates PhysioNet data as a reliable source for ECG studies and arrhythmia detection.

Reference:

- PhysioNet, MIT-BIH Arrhythmia Database (2020).