

DH 307

(Research & Development Project Report)

CHERISH JAIN (22B3937)

**TOPIC: Design of Wearable Device for vital parameter
monitoring**

Guide: Prof. Nirmal Punjabi

INTRODUCTION:

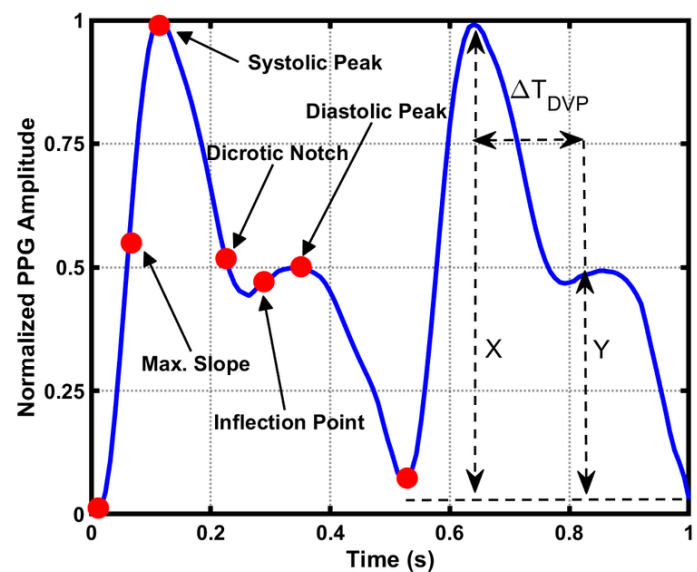
Measuring Vital parameters such as Heart rate, Blood pressure, stress rate, sleep rate is the need of the hour, especially for nursing homes as measuring these parameters continuously helps give an overview of their health in detailed way. But the current methods such as ECG, or classical methods of measuring BP requires hardware and connections in the body which may irritate people. Many times it is seen that people suffer heart attack while sleeping and there are no prior symptoms. To mitigate this issue, there exists a non-invasive method of measuring signals called as PHOTOPLETHYSMOGRAPHY, commonly known as PPG.

A Bried about Photoplethysmography:

Photoplethysmography (PPG) is a non-invasive technique utilized to gauge fluctuations in blood volume within the skin's microvascular bed. This method relies on optical characteristics like absorption, scattering, and transmission properties of the human body when exposed to particular light wavelengths. The term "PPG" originates from the fusion of "photo," representing light; "**plethysmo**," denoting volume; and "**graphy**," indicating recording. There exists many methods to measure this, most of the smart watches today utilize this

to monitor your health and provide an detailed analytic review which you can see on your smart phones. PPG records the amount of light transmitted or reflected by the change in concentration of substances in the blood and the optical path according to pulsation, which can be explained by the Beer–Lambert law.

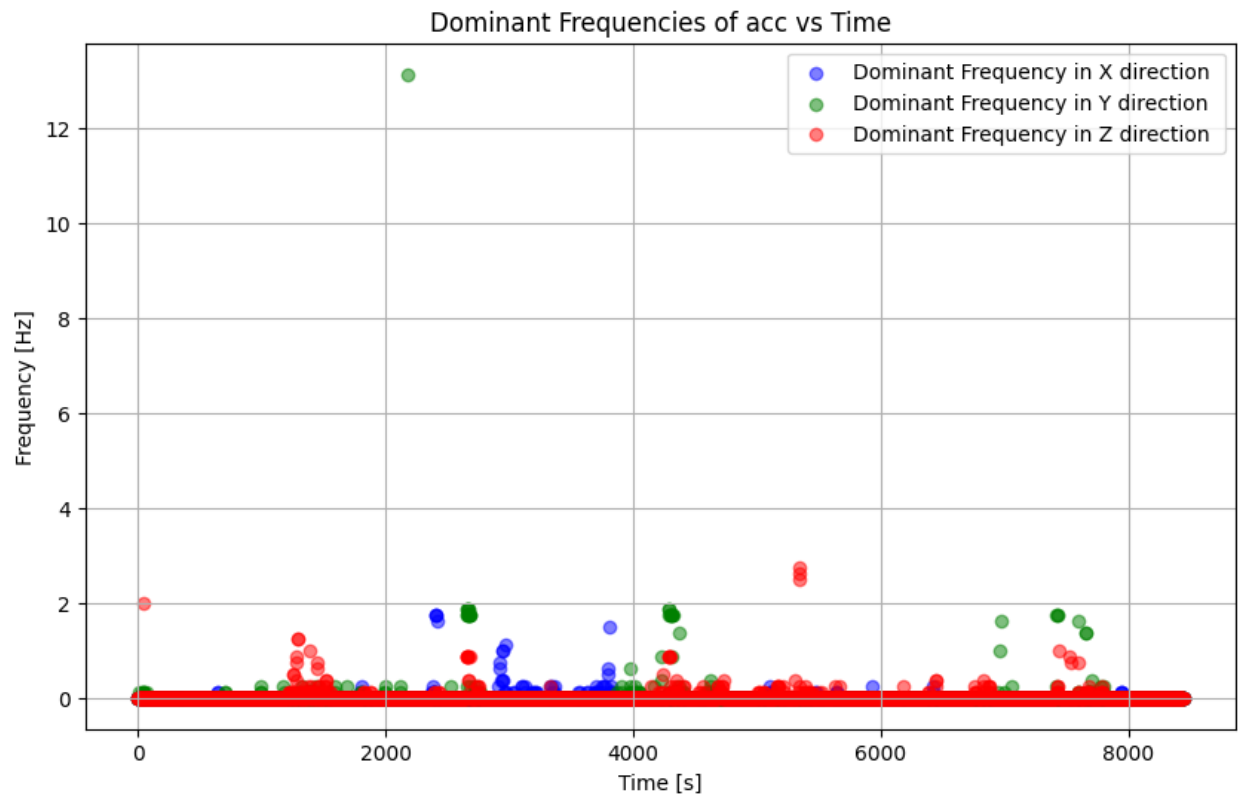
The Beer-Lambert law, encapsulated by the equation $I = I_0 e^{-\epsilon lc}$, elucidates how the intensity of light transmitted (I) through a medium diminishes exponentially concerning the incident light intensity (I_0), absorption coefficient (ϵ), optical path length (l), and concentration of the medium (c). Absorbance, represented as $-\epsilon lc$, quantifies this attenuation. In the context of skin layers, the collective absorbance is the summation of individual layer absorbances ($A_k = -\epsilon_k c_k l_k$), where ϵ , c , and l denote the extinction coefficient, concentration, and optical path length, respectively.



1. Motion artifact problem in PPG

PPG-based devices such as pulse oximeters exhibit optimal performance when the subject remains at rest. However, real-life scenarios often involve subjects who may not maintain stillness, leading to signal distortion, particularly during involuntary movements like shivering. Recognizing the widespread adoption of PPG in portable and wearable devices, significant efforts have been directed towards enhancing PPG signal accuracy, especially in the presence of subject movement.

Among various strategies employed to address this challenge, a common approach involves concurrent measurement of motion using accelerometers or similar transducers. By independently capturing subject motion, it becomes feasible to develop models that accurately characterize movement artifacts, facilitating their effective removal from the PPG signal. There are various classical methods to mitigate the issue of motion artifacts. One such is described below.



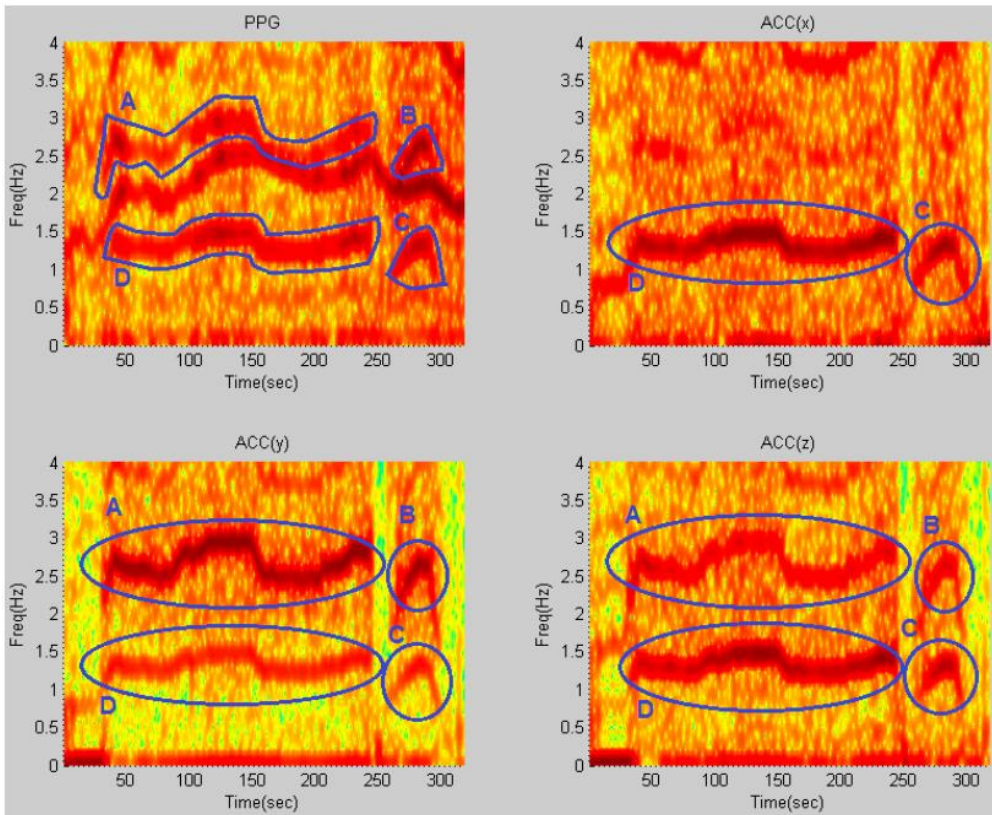
SPaMA Algorithm & PPG-Dalia Dataset

Accurately estimating heart rates from PPG signals during intense physical activity is challenging due to motion artifacts. Spectral filter algorithm for Motion Artifacts and heart rate reconstruction, (**SPaMA**) is a novel algorithm employing time-varying spectral analysis to reconstruct motion-corrupted PPG signals and determine heart rates. By comparing PPG and accelerometer data spectra, SPaMA effectively identifies and removes motion-induced frequency peaks, enabling more accurate heart rate estimation.

The dataset on which this algorithm was applied was **PPG-DaLiA Dataset**. It comprised of 8 participants out of which we have applied this algorithm on 1 of the participants (S1). Each of the participant underwent a series of activities listed below: A brief overview about this algorithm has been given on the next page.

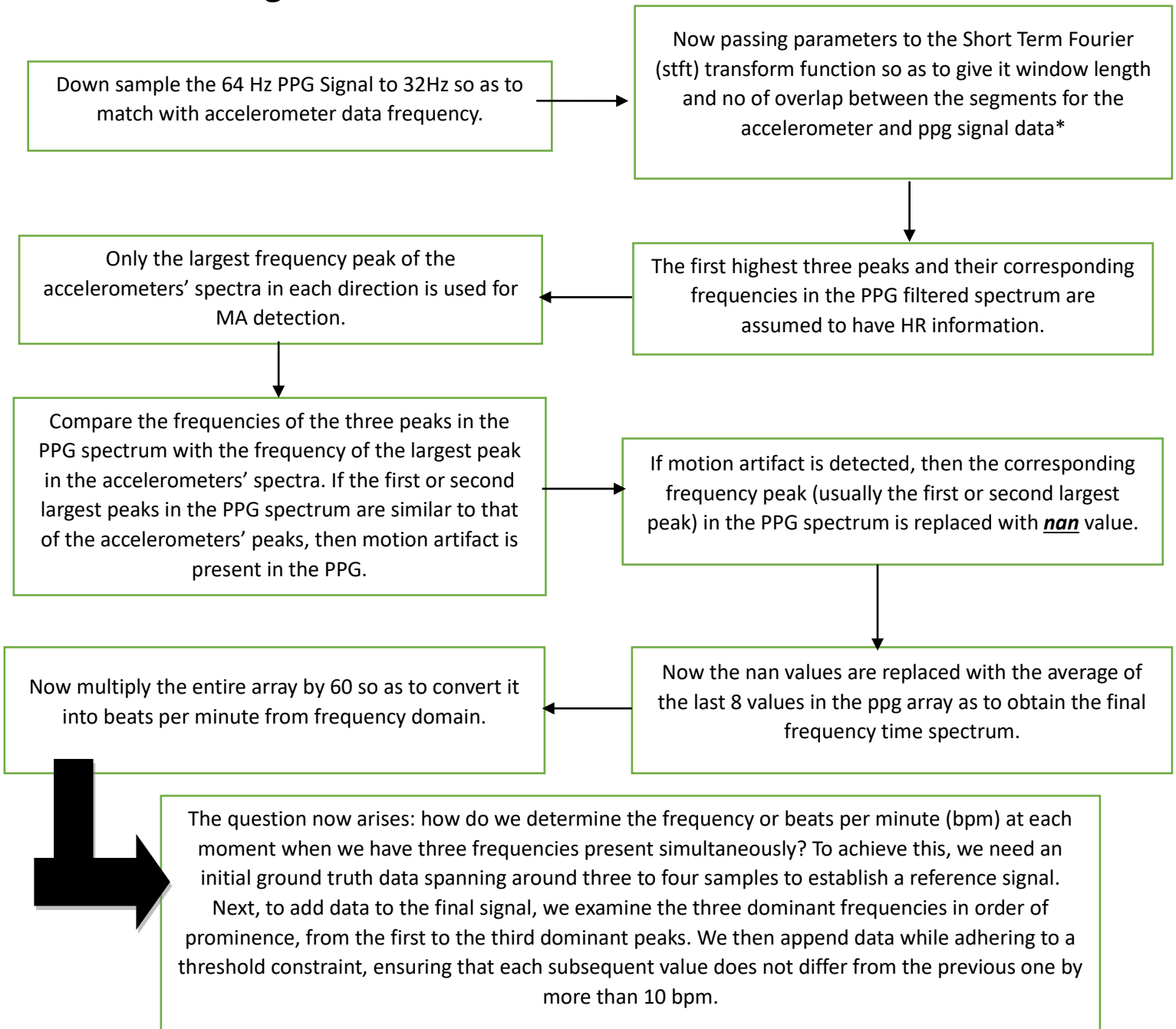
Activity	Duration [min] (Total duration = 2.5hrs)
Sitting still	10
Ascending/Descending stairs	5
Table Soccer	5
Cycling	8
Driving car	15
Lunch break	30
Walking	10
Working	20

Following Diagram Explains Idea behind SPaMA Algorithm:



Time-frequency spectra of recording from a dataset: (Top-Left) TF spectrum of PPG; (Top-Right) TF spectrum of ACC(x); (Bottom-Left) TF spectrum of ACC(y); (Bottom-Right) TF spectrum of ACC(z); all computed from stage (I) of the algorithm. Blue circles and letters represent movement elements in all 4 spectra.

SPaMA Algorithm Flowchart:



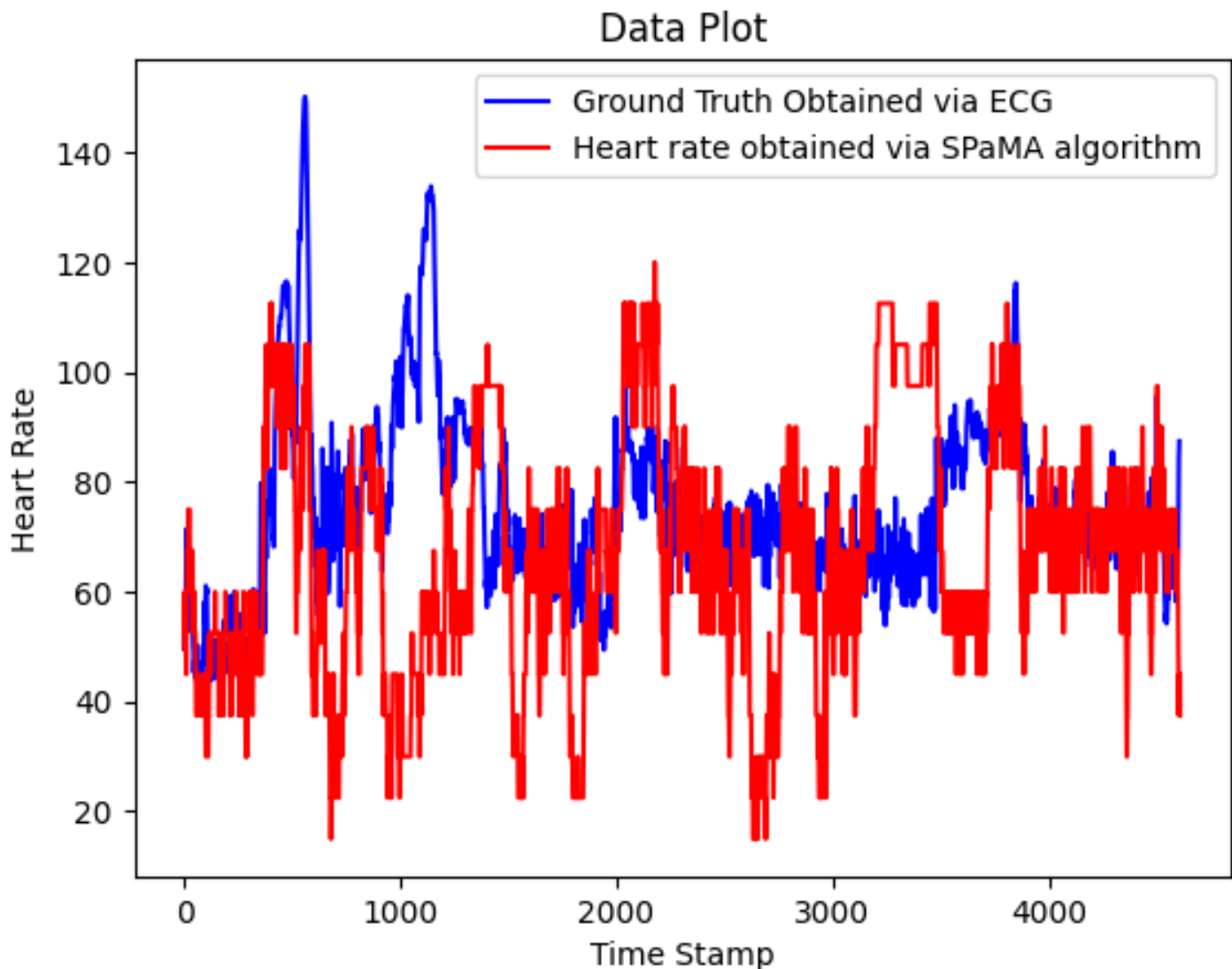
A brief about the PPG-DaLiaDataset:

DataName	Device Name	Sampling Frequency
1. ECG	RespiBAN Professional (a chest-worn device)	700Hz
2. 3-axis accelerometer	RespiBAN Professional (a chest-worn device)	32Hz
3. PPG data	Empatica E4 (a wrist-worn device)	64Hz

Results & Remarks on SPaMA Algorithm:

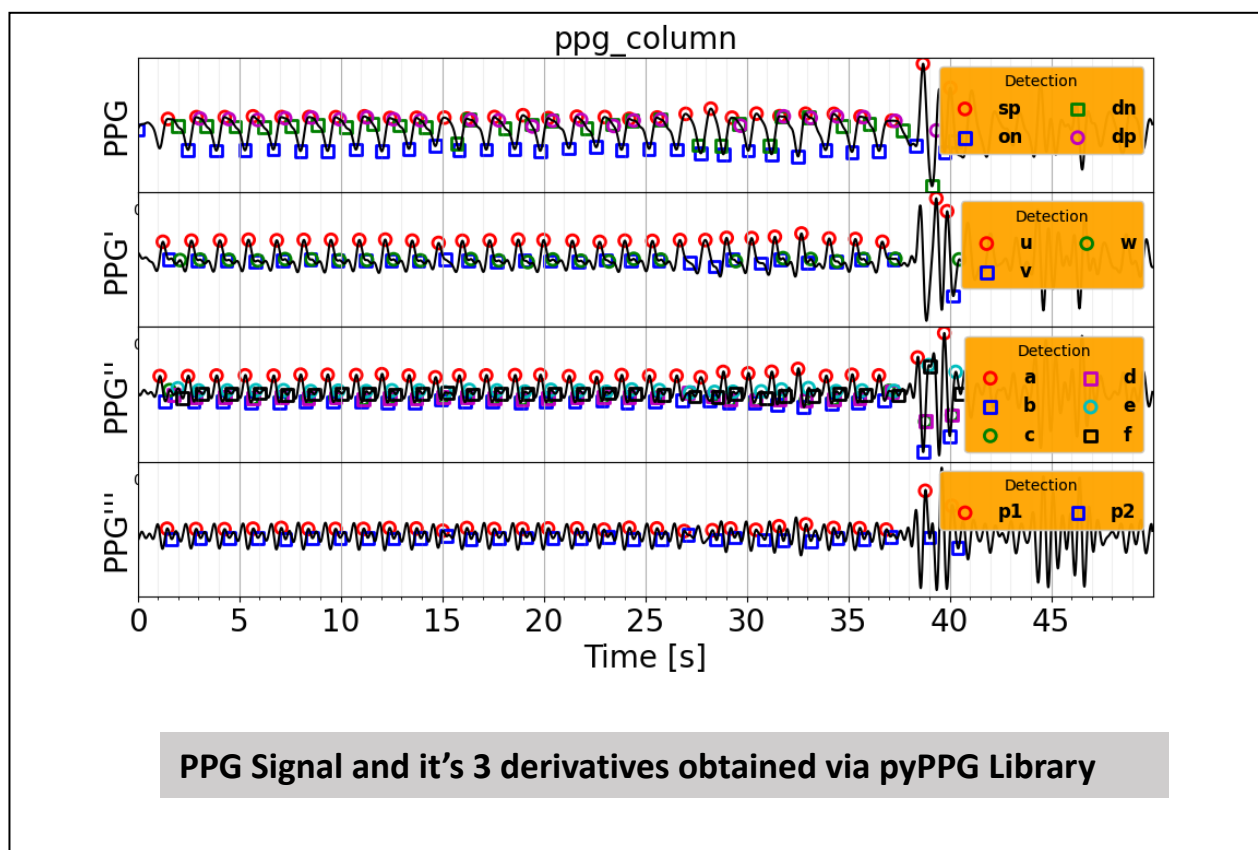
I obtained a **Mean Absolute Error of 20.26 beats per minute** on this participant. The dataset research (PPG DaLia) paper claims that they obtained an error of **11.86 bpm**. The difference may be due to the parameters which they passed while computing the STFT (window such as Hann/ Rectangular, I had used Hann window) or due to the number of initial reference values which they gave while obtaining the Time-Frequency spectrum. There is a future scope to obtain back time series via Inverse fourier transform and then apply the below described library/ methods to further apply Machine Learning.

The mean heart rate obtained was **67.019 beats per minute** on the entire 2.5 hr dataset



2. pyPPG LIBRARY

Goda et al had release a python toolbox very recently which is useful for obtaining some standard parameters from the PPG Signal which can be used to pass in various different Machine Learning Models. It can be used on the ppg signal in various ways such as for Prefiltering, Onset detection, Peak detection, Biomarkers, Obtaining SQL, Biomarker engineering (functions of Biomarkers). These Biomarkers when passed directly in machine learning models such as Random Forest or CNN gives excellent results as compared to the Classical Methods.



The pyppg library calculates upto 3 derivatives of the ppg signal which are used to obtain various important fiducials point. A small part of a stable PPG Dalia data is shown above by passing it in the pyPPG Library.

Following fiducial points are extracted by this library which are used in this project:

FIDUCIAL POINT	DESCRIPTION
Ts	Time span from onset to systolic peak
Tsd	Time span from systolic peak to diastolic peak
Td	Time span from systolic peak to the next onset
Tc	Time span between two successive onsets
Ts75	Time span from onset to 75 percent of PPG amplitude at systolic peak, similar symbol has the same meaning
A1	Pulse area under PPG curve between onset and diastolic peak
A2	Pulse area under PPG curve between systolic peak and the next onset

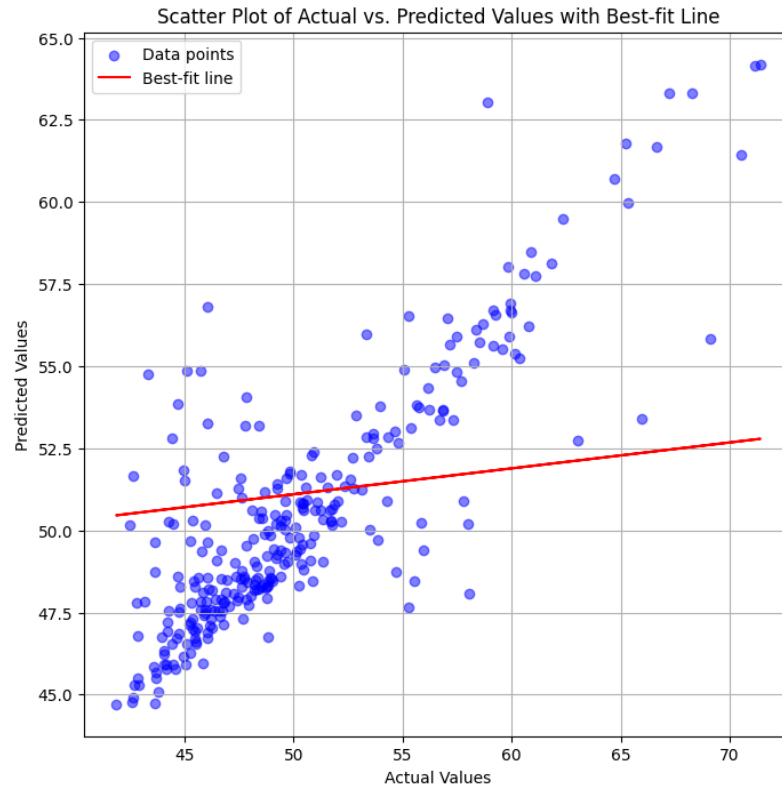
I applied the machine learning approach by passing ppg signal into this library and obtaining various biomarkers. The used biomarkers are described below.

After obtaining the biomarkers I applied Random Forest machine learning model on the engineered biomarkers and trained it.

Engineered biomarker	Description
F1	Tsd
F2	$(Td75 - Ts75)/Tc$
F3	$A1/(Ts + Tsd)$
F4	$A2/Td$
F5	Tv
F6	Ts/Td
F7	Td50
F8	$Ts + Tsd$

The above-described methodology was applied on the dataset
Following were the results obtained :

Dataset Name	MAE error in heart rate	Standard Deviation in heart rate
PPG DaliA dataset	2.413 bpm	3.77 bpm



Results Obtained on PPG DaliA dataset on the part
where the participant was stable

Conclusion & Future Scope

The SPAMA algorithm's performance isn't optimal due to its reliance on classical signal processing techniques, unlike the more advanced methodologies such as CNNs and Transformers in machine learning. There's significant potential for improvement in this field by integrating SPAMA for motion artifact removal and PPG signal reconstruction, followed by the application of machine learning models. This approach leverages the strengths of both machine learning and classical Fourier transform methods.

Major References used:

- 1) [SPAMA Algorithm research paper](#)
- 2) [PPG DaLia Dataset Research paper](#)
- 3) [Machine Learning Methods for obtaining Vital Parameters](#)

COLAB NOTEBOOKS LINK:

- 1) [Machine Learning Methodology on PPG Dalia Dataset Colab Notebook](#)
- 2) [SPAMA Algorithm Processing Colab Notebook](#)

.....