Frequency Analysis of ECG signal

2EC502 DSP Sessional Assignment

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Abstract

The Combination of P-wave, T-wave and QRS-Complex is known as one complete cardiac cycle of Electrocardiogram(ECG) Signal. Electrocardiograph indicates the Electrical activities of Heart during the Polarization and Depolarization activity. ECG is plotted on chart(graph) paper and also stored in computer(.dat or .ecg or .hea) for the analyzing purpose in the future. The cost of ECG test is very much high. And the reason is, It requires automated ECG signal analysis techniques with the help of computerized classification which gives pretty accurate, fast and reliable detection of the disease.

Frequency Analysis & Data analysis are very much useful methods for a Biomedical Engineering research. In this paper we will be describing the frequency analysis of electrocardiogram(ECG). And in this paper we will also be discussing about the three different heart rate frequency detection algorithms. The Algorithms will be based on the statistical and different mathematical theories.

Keywords- Electrocardiogram(ECG) Signal; Standard Lead Arrangement; Heart Disease; ECG Datasets.

Contents

❖ <u>Introduction</u>

ECG is a three letter acronym for Electrocardiography. It has been derived from greek words (electro + cardio + graph) means (electricity + heart + write). In simple words "Electrocardiography is the graphical representation of Electrical currents of the Heart".
ECG is composite from 5 waves - P, Q, R, S and T. This signal can be measured by electrodes from the human body in typical engagement. Signals from these electrodes are brought to simple electrical circuits with amplifiers and ADC(Analog to Digital Converter).
The Heart Rate is very much important to check the health status. The frequency measurement is a very useful medical and sports application. One of possible ways to get the heart rate frequency is to compute it using ECG Signal. And it can be done by many different ways and algorithms.

❖ What is Electrocardiogram ?

It is transthoracic interpretation of the electrical activity of the heart over the time captured and externally recorded by skin electrodes.

"An ECG is an diagnostic tool, not a treatment". **NO ONE IS EVER CURED BY ECG.**

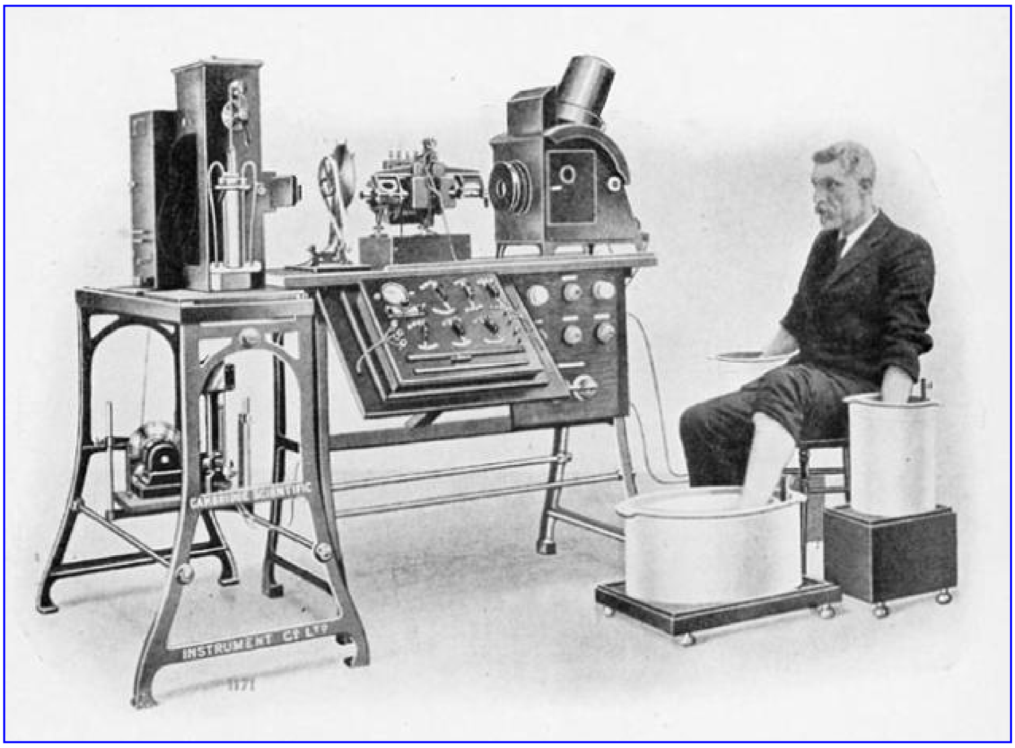


Image 1 : Einthoven recording his first ECG in 1902 by placing limbs in buckets of conducting solution

❖ Biological View

✧ Basic Electrophysiology

Physiological Properties of Myocardial Cell

1. **Automaticity :** Ability to initiate an Impulse.
2. **Excitability :** Ability to respond to a Stimulus.
3. **Conductivity :** Ability to transmit an Impulse.
4. **Contractility :** Ability to respond with pumping action.

Depolarization and repolarization of a cardiac cell generates action potential.

✧ Electrical Conduction System of Heart

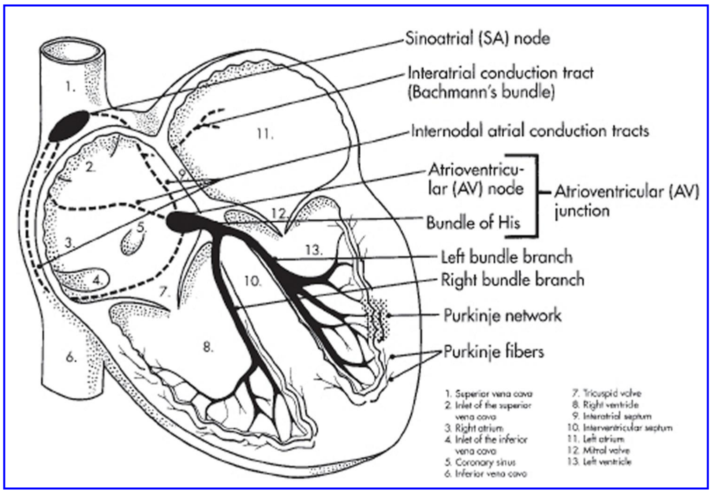


Image 2 : Heart Electrical System
Courtesy : Google

1. Each Cardiac Cycle starts electrically discharging from **Right Atrium** i.e. Sinotrial (SA) Node.
2. Depolarization spreads through the atrial muscle fibers.
3. There is a delay while polarization spreads through another special area in the atrium, the atrioventricular (AV) mode.
4. Thereafter the electrical discharge travels very rapidly, down specialized conduction tissue : First a single pathway, the 'bundle of his' which then divides in the septum between the septum between the vetricles into the right and left bundle branches.
5. Within the ventricular mass, conduction spreads somewhat moreslowly, through the specialized tissue called 'Purkinje Fibres'.

Table 1 : Conduction Speed of Cardiac Tissue

Tissue	Conduction Rate (m/s)
SA Node	0.05
Atrial Pathway	1
AV Node	0.05
Bundle of His	0.05
Purkinje System	4
Vetricular Muscle	1

✧ Normal Sinus Rythem

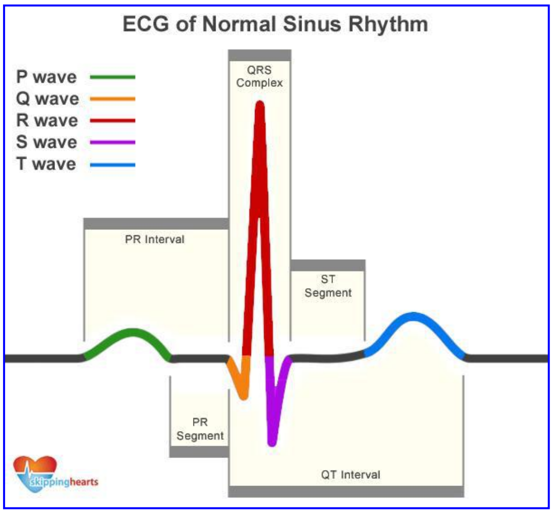


Image Courtsey : skippinghearts

The above figure depicts Normal Sinus Rythem, it comprises of following waves :

1. **P Wave :** Denotes the Atrial Depolarization (electrical vector is directed from the SA node towards the AV Node)
2. **QRS Complex :** Denotes the depolarization of ventricles as well as re-polarization of atrium.
3. **T Waves :** Denotes the re-polarization (or recovery) of ventricles. The interval from the beginning of the QRS to the apex of the T wave is referred to as the **Absolute Refractory Period.** The last hart of the T wave is referred to as the **Relative Refractory Period.**
4. **PR Interval :** Beginning of the P wave to the beginning of the QRS Complex.
5. **ST Segment :** Connects the QRS complex to the T-wave.
6. **QT Interval :** The Beginning of QRS Complex to the end of the T-wave.

✧ Segment v/s Interval

✓ A Segment is the straight line connecting two waves.
✓ An interval encompasses at least one wave plus the connecting straight line.

I. J Point : It is the point where the QRS Complex meets the ST Wave.

II. J Wave

✓ It is also known as a camel hump sign, late delta waves, Hathook Junctions, Hypothermic Wave, Prominent J wave, K wave, H wave or current of injury.
✓ Positive deflection occurring at the junction of QRS complex and ST Segment(J point).
✓ Observed in people suffering from hypothermia with a temperature of less than 32.

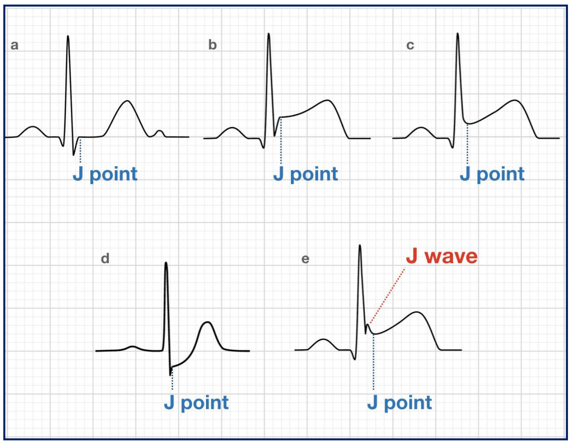


Image 3 : J Wave in a Hypothermic Individuals
Courtesy : Google

III. **U Wave**

- ✓ Typically small, by definition it follows the T-Wave.
- ✓ Prominent U waves are the most often seen in Hypokalemia, but may be present in Hypercalcemia and Thyrotoxicosis.

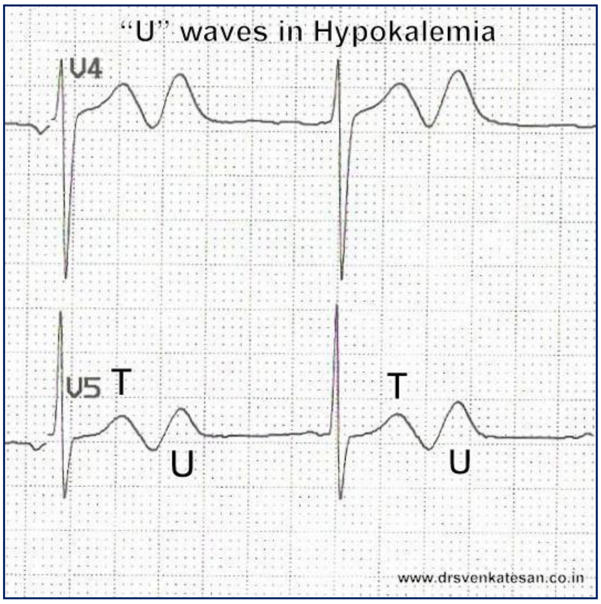


Image 4 : U Wave in Hypokalemic Individual
Courtesy : www.drsvenkatesan.co.in

✧ ECG Graph Paper

- ✓ Runs at the speed of 25mm/sec.
- ✓ Each small box of ECG paper is 1mm square.
- ✓ At a paper speed of 25mm/s, one small block equals 0.04 seconds.
- ✓ Five small blocks makes one large block which translates into 0.20 seconds.
- ✓ Hence, there are 5 large blocks per second.
- ✓ Voltage 1 mm = 0.1 mV. Between each individual block vertically.

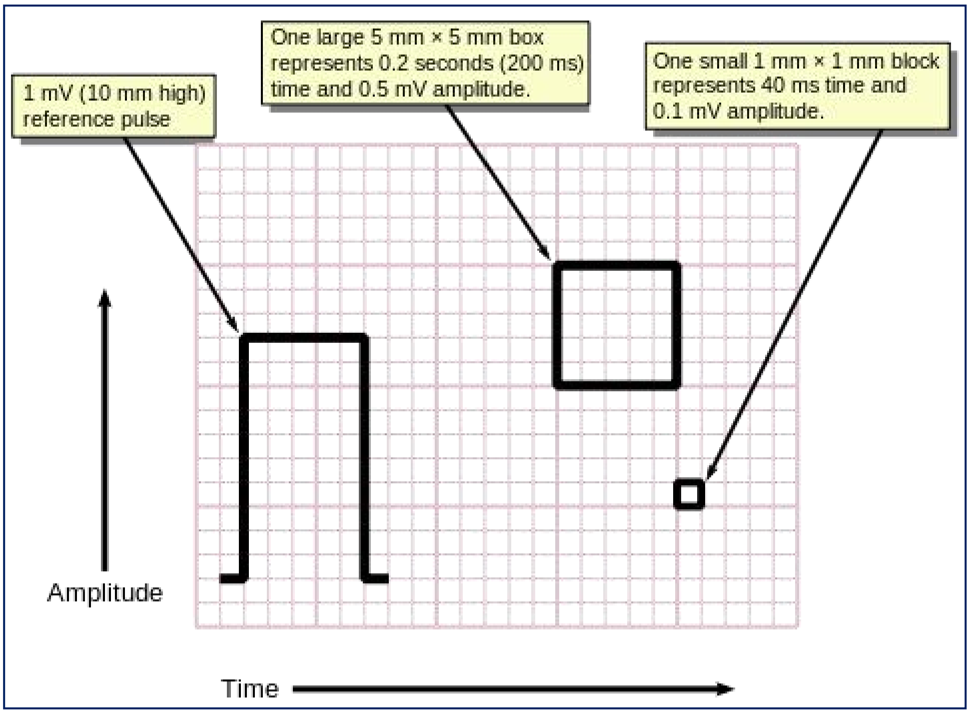


Image 5 : ECG Graph Paper
Courtesy : Bing Images

Table 2 : Abnormalities

Abnormality	**Characteristics**
Bradycardia	R-R Interval > 1s
Tachycardia	R - R Interval < 0.6s
Hypercalcaemia	QRS Interval < 0.1s
Dextrocardia	Inverted P-wave
Hyperkalemia	Tall T-wave and absence of P-wave
Sudden Cardia Death	Irregular ECG
Sinoatrial Block	Complete drop out of cardiac cycle
Miocardial Ischemia	Inverted T-wave

❖ Signal Acquisition

Digital Signal Processing and Heart Rate calculation of the ECG signal can be acquired by measurement card with sampling frequency fs = 500 Hz. And this sampled signal was used as input signal for the digital filters and the heart rate detection algorithms designing and testing.

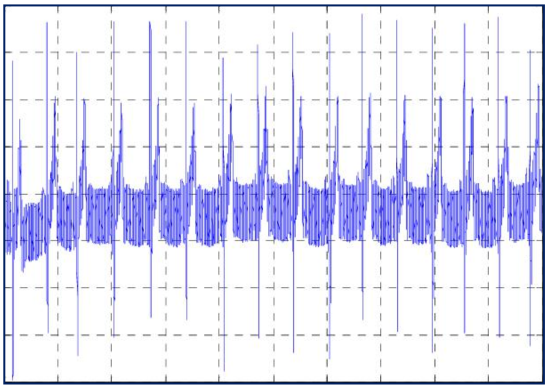


Image 6 : Raw Signal
Courtesy : Bing Images

❖ Frequency Analysis of ECG Signal

Signal Processing and Analysis of ECG signal has always been an interesting topic from many years and still research is going on in this field. Many different methods have already been developed for ECG analysis, such as Fast Fourier transform, Short time Fourier transform, etc.

✧ Fast Fourier Transform

In earlier days Time Domain Method was used for the ECG Signal Analysis. But it was not sufficient to study all the characteristics of ECG Signal. So, the new method named FFT is been introduced. Fourier Transform is well known for transformation of Time Domain Signal to Frequency Domain to obtain the frequency coefficients. It is much faster and more capable algorithm to work out the DFT and obtains the same effect. FFT is defined by the formula :

$$X_k = \sum_{n=0}^{N-1} x e^{-nk2\pi i/n} \qquad \text{....................(1)}$$

Where k is an integer ranging from 0 to N-1. ECG signals can be compressed by using variety of techniques. One of the most important techniques is FFT. The process is consisting of :

- ✓ Obtaining an ECG sample or input signal.
- ✓ Compressing the input signal by removing the low frequency components.
- ✓ Recovery of the original signal by using inverse FFT

But the FFT fails to provide the information regarding the accurate location of frequency components in time.

✧ Short Time Fourier Transform

It is developed by Dennis Gabor in 1946 to overcome the limitations of FFT. STFT is consisting of both Time and Frequency information. The Spectrogram based on STFT is a very simple and fast technique in comparison to other time–frequency analysis. It is an easy approach of slicing the waveform of our interest into a large number of short-segments. Then it analyzes each segment using standard Fourier transform.

Short Time Fourier Transform : In this method, A window function is applied to a segment of data, efficiently isolating that segment from the overall waveform, and then Fourier transform is applied to that segment.
For a signal x(t), the definition of STFT can be given as :

$$X(\tau, f) = \int_{-T/2}^{T/2} x(t) w(t - \tau e^{-i2\pi ft}) dt \qquad \text{(2)}$$

Where, w(t) is the window with Duration = T and Centered at time location t.
STFT = Fourier Transform of windowed Signal **x(t)w(t-τ)**

Limitation : Its time frequency precision is not optimal.

So, To overcome this drawback we will be looking for more suitable technique. i.e. Wavelet Transform.

❖ Wavelet Transform

The Concept of wavelet was first introduced by the **Jean Morlet** (French geophysicist) in 1982.
Wavelet means Small Wave.
For variety of Applications, there are various Wavelets available which includes :
Biorthogonal, Haar, Coiflet, Symlet, Daubechies Wavelets, etc.
Some features which make them useful are:

- Wavelets are localized in both time and frequency.
- For analyzing non-stationary signals such as ECG which have frequent level variations and uneven features.
- Wavelet separates a signal into Multi Resolution components.

The Wavelet Transform is a linear process that decomposes the signal into a number of scales associated with frequency components and analyzes each scale with a certain resolution. One of the major advantages of Wavelet technique is that many different Wavelet functions are available and that allows user selecting the best function for analyzing the signal, whereas in the case of Fourier analysis it is restricted to one feature morphology that is the sinusoidal.

Wavelet transforms can be classified into two categories:
Continuous Wavelet Transforms (CWT)
Discrete Wavelet Transforms (DWT)

✧ Continuous Wavelet Transform

It is the method for Time-Frequency Analysis. It differ from the conventional method STFT in the only case that "It allows high localization in time of high frequency signal features"
The CWT of a signal x(t) is defined as :

$$W(a,b) = 1/\sqrt{a} \int_{-\infty}^{\infty} f(t) h^*((t-b)/a) dt \qquad \text{(3)}$$

Where, h(t) is mother wavelet
a is scaling parameter in y-axis
b is the shift parameter in x-axis

✧ Discrete Wavelet Transform :

The DWT is defined as :

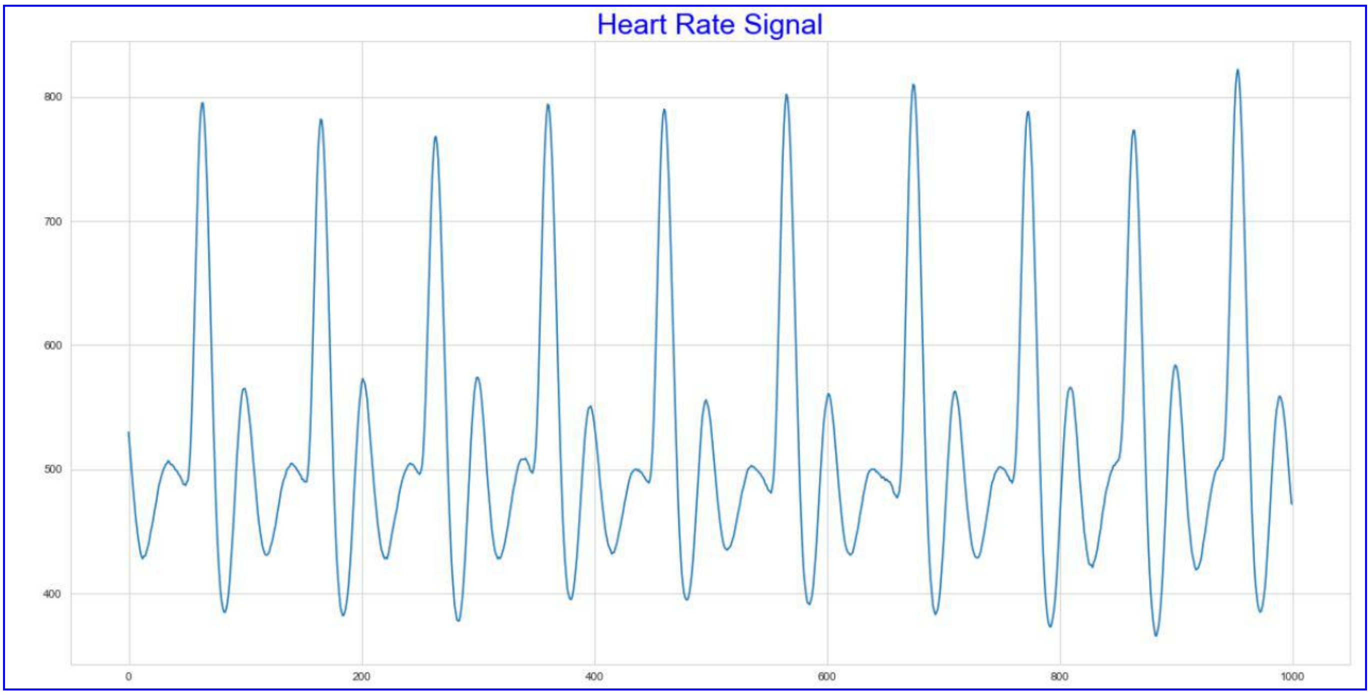
$$W(j,k) = \sum_j \sum_k x(k) e^{-\frac{j}{2}} \Psi(2^{-j} n - k)$$

Where Ψ(t) is a time function with finite energy and fast decay called the mother of wavelet.

❖ Python Implementation

Code 1 : To Plot the ECG signal

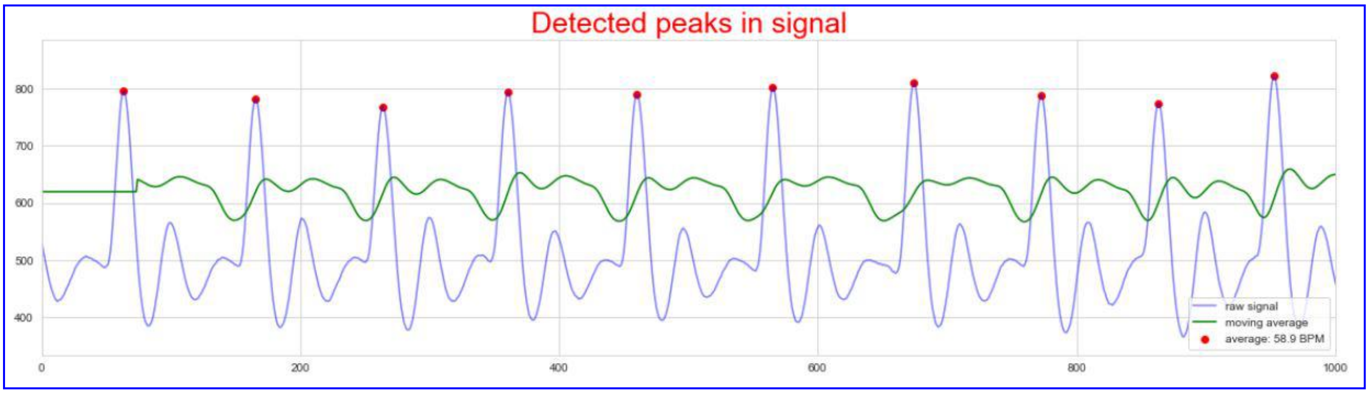
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

dataset = pd.read_csv("data.csv") #Read data from CSV datafile

%matplotlib inline
plt.rcParams['figure.figsize'] = [20.0, 10.0]  # Bigger figures
sns.set_style("whitegrid")  # White background

plt.title("Heart Rate Signal",size=25,color='b') #The title of our plot
plt.plot(dataset.hart[:1000]) #Draw the plot object
plt.show() #Display the plot
```



Code 2 : To Detect the Peaks from Signal

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math

dataset = pd.read_csv("data.csv")

#Calculate moving average with 0.75s in both directions, then append do dataset
hrw = 0.75 #One-sided window size, as proportion of the sampling frequency
fs = 100 #The example dataset was recorded at 100Hz

mov_avg = dataset['hart'].rolling(int(hrw*fs)).mean() #Calculate moving average
#Impute where moving average function returns NaN, which is the beginning of the signal where x hrw
avg_hr = (np.mean(dataset.hart[:1000]))
mov_avg = [avg_hr if math.isnan(x) else x for x in mov_avg]
mov_avg = [x*1.2 for x in mov_avg]
dataset['hart_rollingmean'] = mov_avg #Append the moving average to the dataframe

#Mark regions of interest
window = []
peaklist = []
listpos = 0 #We use a counter to move over the different data columns
```

```
for datapoint in dataset.hart:
    rollingmean = dataset.hart_rollingmean[listpos] #Get local mean
    if (datapoint < rollingmean) and (len(window) < 1): #If no detectable R-complex activity -> do nothing
        listpos += 1
    elif (datapoint > rollingmean): #If signal comes above local mean, mark ROI
        window.append(datapoint)
        listpos += 1
    else: #If signal drops below local mean -> determine highest point
        maximum = max(window)
        beatposition = listpos - len(window) + (window.index(max(window))) #Notate the position of the point on the X-axis
        peaklist.append(beatposition) #Add detected peak to list
        window = [] #Clear marked ROI
        listpos += 1

ybeat = [dataset.hart[x] for x in peaklist] #Get the y-value of all peaks for plotting purposes

plt.title("Detected peaks in signal",size=25, color='red')
plt.xlim(0,1000)
plt.plot(dataset.hart, alpha=0.5, color='blue', label="raw signal") #Plot semi-transparent HR
plt.plot(mov_avg, color ='green', label="moving average") #Plot moving average
plt.scatter(peaklist, ybeat, color='red', label="average: %.1f BPM" %bpm) #Plot detected peaks
plt.legend(loc=4, framealpha=0.8)
plt.show()
```



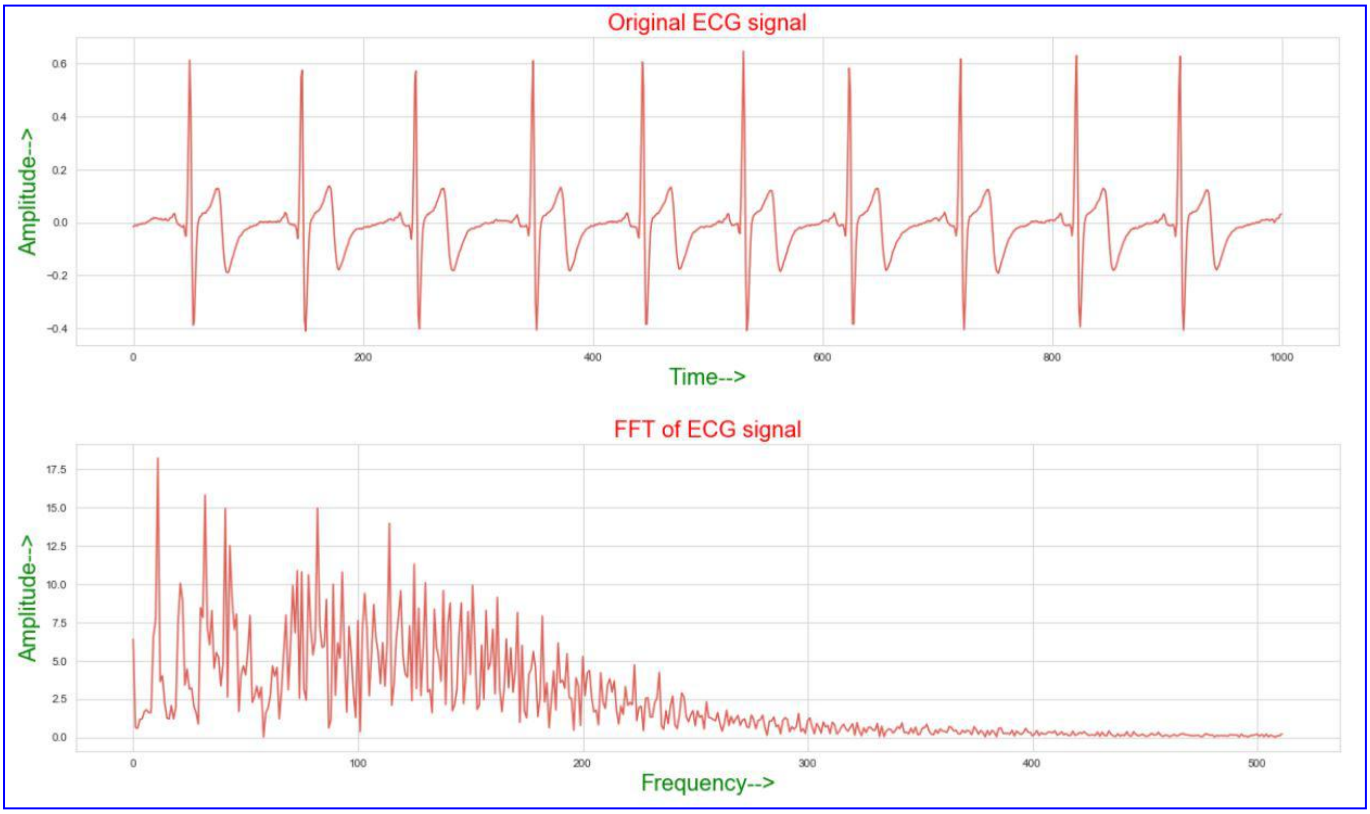
Code 3 : To get the "Average Bit Per Minute"

```
RR_list = []
cnt = 0

while (cnt < (len(peaklist)-1)):
    RR_interval = (peaklist[cnt+1] - peaklist[cnt]) #Calculate distance between beats in # of samples
    ms_dist = ((RR_interval / fs) * 1000.0) #Convert sample distances to ms distances
    RR_list.append(ms_dist) #Append to list
    cnt += 1

bpm = 60000 / np.mean(RR_list) #60000 ms (1 minute) / average R-R interval of signal
print("Average Heart Beat is: %.01f" %bpm) #Round off to 1 decimal and print
```

✧ **Result :** Average Heart Beat is: 58.9

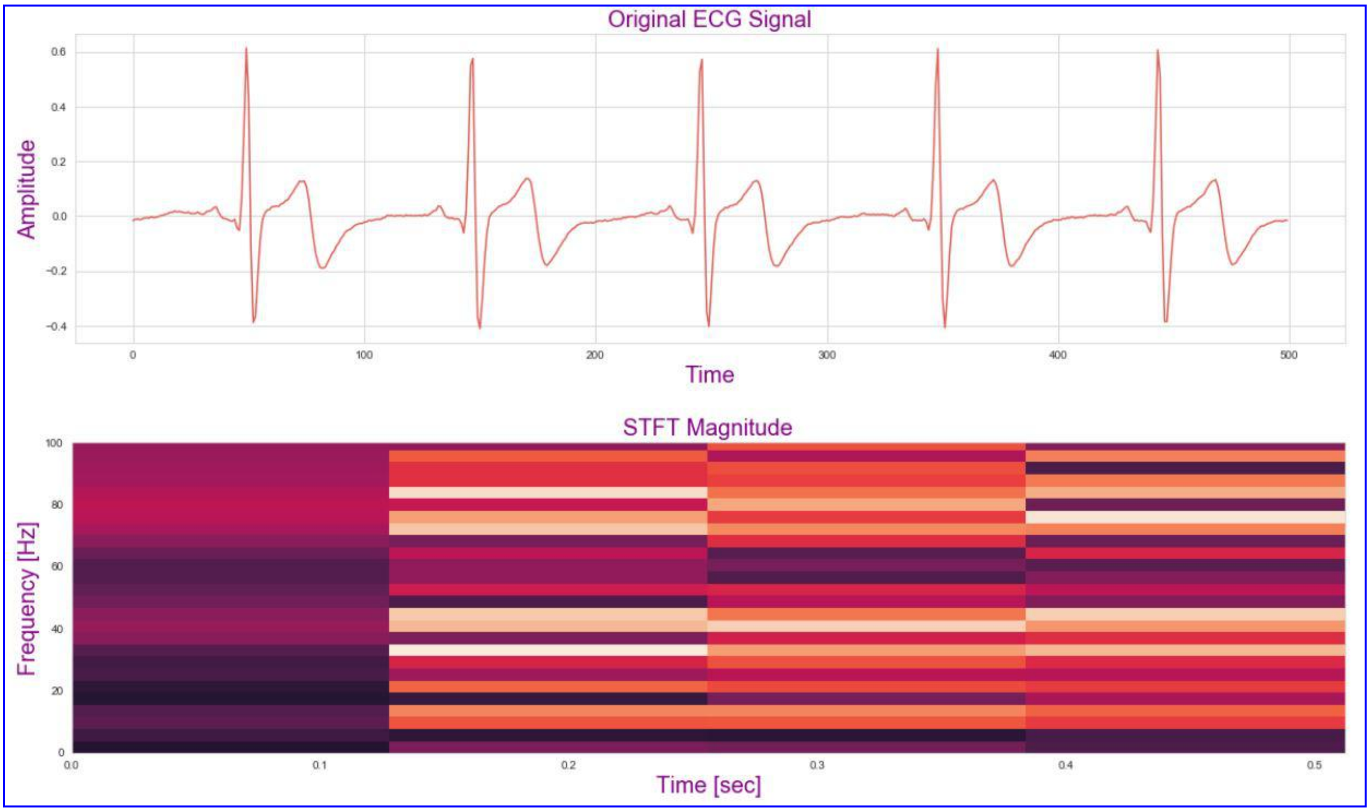
Code 4 : Fast Fourier Transform on ECG

```
%matplotlib inline
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.gridspec as GridSpec
from scipy.fftpack import fft

%matplotlib inline
plt.rcParams['figure.figsize'] = [20.0, 5.0]  # Bigger figures
sns.set_style("whitegrid")  # White background
sns.set_palette(sns.color_palette("hls"))  # Better colours

df = pd.read_csv("https://raw.githubusercontent.com/neuropsychology/NeuroKit.py/master/examples/Bio/bio_100Hz.csv")

ECG_FFT = np.abs(fft(df.ECG[:1000], 1024))
ECG_FFT2 = ECG_FFT[0:512]
plt.title("Original ECG signal",size=20,color='red')
plt.xlabel("Time-->",size=20,color='green')
plt.ylabel("Amplitude-->",size=20,color='green')
plt.plot(df.ECG[:1000])
plt.show()

#plt.plot(np.abs(ECG_FFT))
#plt.show()

plt.title("FFT of ECG signal",size=20,color='red')
plt.xlabel("Frequency-->",size=20,color='green')
plt.ylabel("Amplitude-->",size=20,color='green')
plt.plot(np.abs(ECG_FFT2))
plt.show()
```



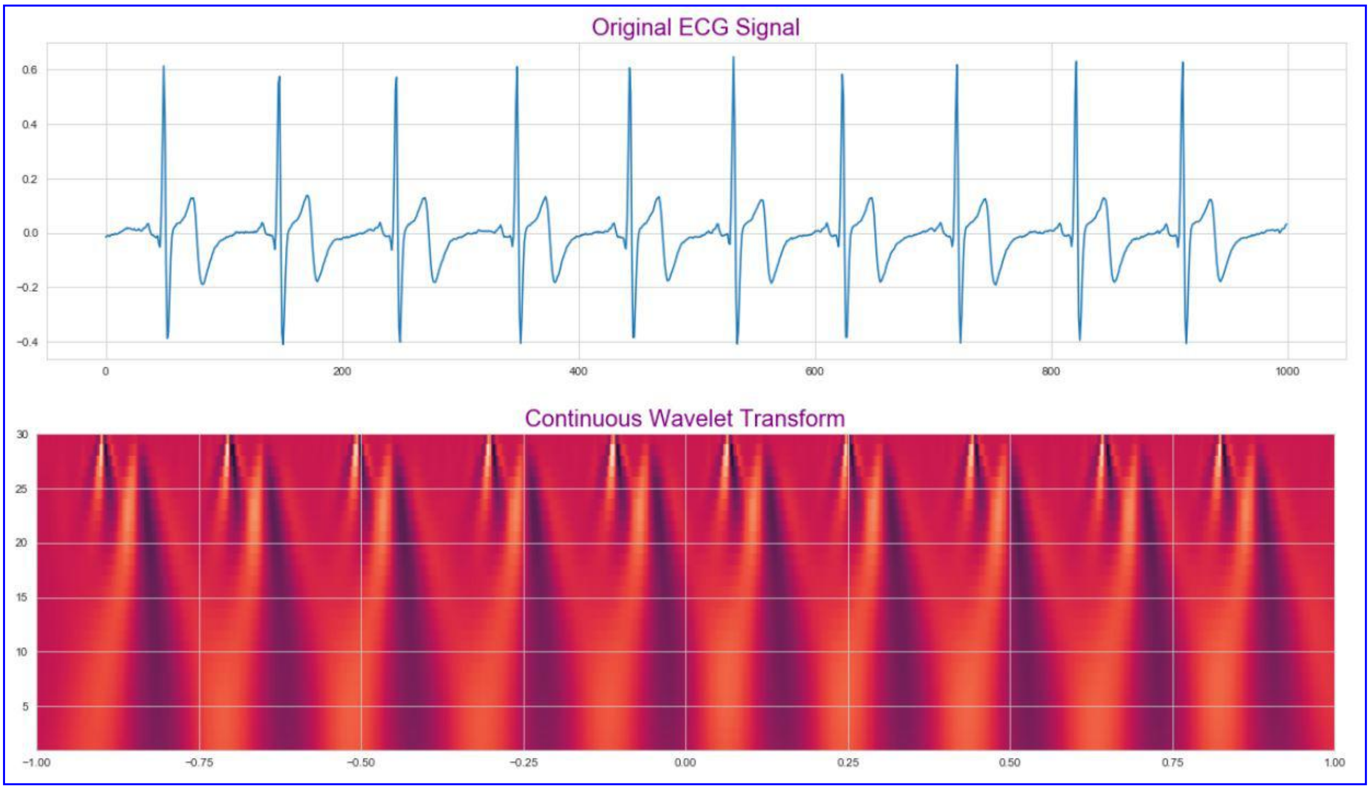
Code 5 : Short Time Fourier Transform on ECG

```
from scipy import signal
import matplotlib.pyplot as plt

%matplotlib inline
plt.rcParams['figure.figsize'] = [20.0, 5.0]  # Bigger figures

fs = 1e3

df = pd.read_csv("https://raw.githubusercontent.com/neuropsychology/NeuroKit.py/master/examples/Bio/bio_100Hz.csv")
f, t, Zxx = signal.stft(df.ECG[:500], fs)

plt.plot(df.ECG[:500])
plt.title("Original ECG Signal",size=20,color='purple')
plt.xlabel("Time",size=20,color='purple')
plt.ylabel("Amplitude",size=20,color='purple')
plt.show()

plt.pcolor(t, f, np.abs(Zxx[:500]))
plt.title('STFT Magnitude',size=20,color='purple')
plt.ylim(0,100)
plt.ylabel('Frequency [Hz]',size=20,color='purple')
plt.xlabel('Time [sec]',size=20,color='purple')
plt.show()
```



Code 6 : Continuous Wavelet Transform on ECG

```
from scipy import signal
import matplotlib.pyplot as plt

%matplotlib inline
plt.rcParams['figure.figsize'] = [20.0, 5.0]  # Bigger figures

t = np.linspace(-1, 1, 200, endpoint=False)
y = pd.read_csv("https://raw.githubusercontent.com/neuropsychology/NeuroKit.py/master/examples/Bio/bio_100Hz.csv")
plt.plot(y.ECG[:1000])
plt.title("Original ECG Signal",size=20,color='purple')
plt.show()

widths = np.arange(1,30)
cwtmatr = signal.cwt(df.ECG[:1000], signal.ricker, widths)

plt.imshow(cwtmatr, extent=[-1, 1, 1, 30], aspect='auto',vmax=abs(cwtmatr).max(), vmin=-abs(cwtmatr).max())
plt.title("Continuous Wavelet Transform",size=20,color='purple')
plt.show()
```



❖ Conclusion :

In this report, I have in have included various techniques that are used to detect the abnormalities of ECG Signal. Out of all this Wavelet Transform is the flexible tool which can be used for signal Analysis.

❖ References

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