In The name of God

University Tehran

Engineering Facility

Electrical and Computer Engineering

Digital Signal Processing

CA2

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Short-Time(Term) Fourier Transform

In this part, we are having the $X_m(\omega)$ for every part, and as we know, it is calculated with this equation:

$$X_m(\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-mR]e^{-j\omega n} = DTFT_\omega\big(x \times SHIFT_{mR}(\omega)\big)$$

As we can see from the equation if we have $X_m(\omega)$ and under a certain condition of m & R we can reconstruct the $x[n]$.

It is clear that if we want to make the signal again we need to have all the information form the signal and that includes $X_m(\omega)$ & m & R as you can see we need everything from the signal. That includes the window size, the hop length and the frequency domain of the signal.

Spectrogram

In this part we read the two audio file and plot the result from them.

The First spectrogram belongs to "$a4.wav$"

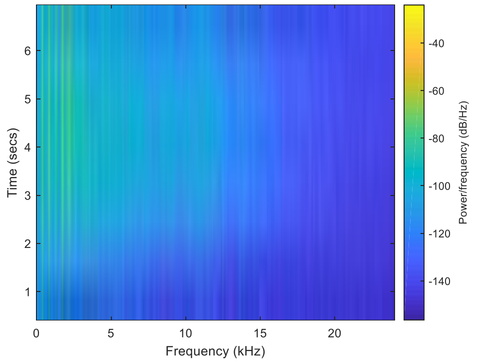

Figure 1

The second spectrogram belongs to "$b4.wav$"

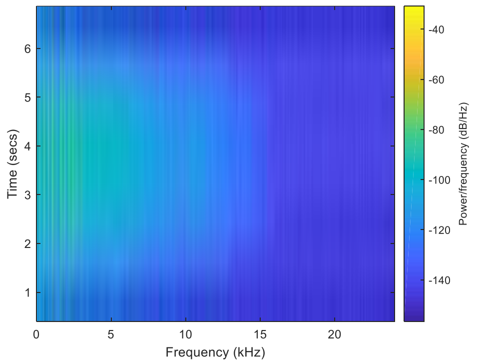

Figure 2

As we can notice from the spectrogram record b4 starts sooner compared to a4 because of the spectrogram we can see that is started in a sooner time.

We assumed every parameter as:

```
Nx = length(x);
nsc = floor(Nx/4.5);
nov = floor(nsc/2);
nff = max(256,2^nextpow2(nsc));
spectrogram (x, hamming(nsc), nov, nff, Fs);
```

Comparing window-size:

We plot the two result of the spectrogram

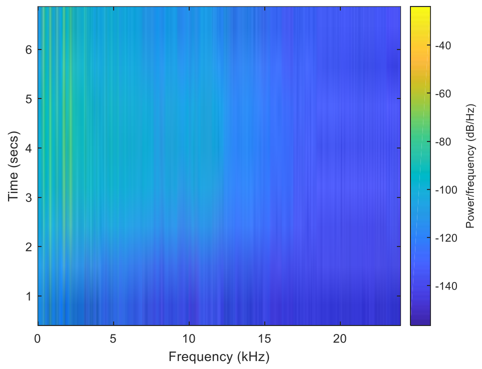

Figure 3 hamming(nsc)/40

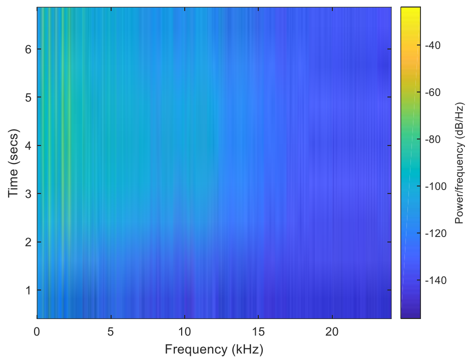

Figure 4 hamming(nsc)*40

Comparing overlap:

In this part we tried two different value for nfft:

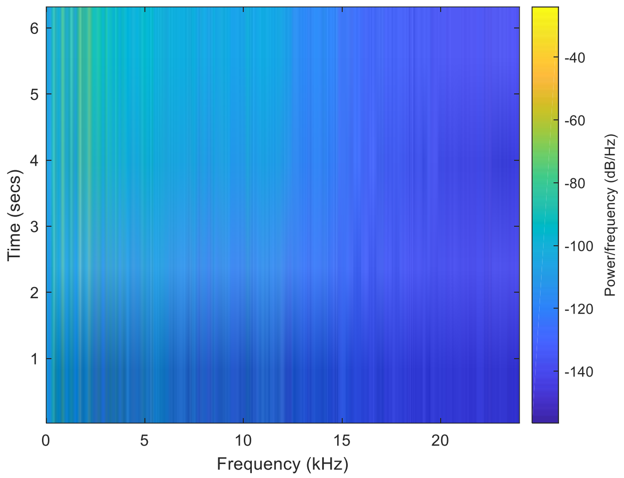

Figure 5 overlap=2000

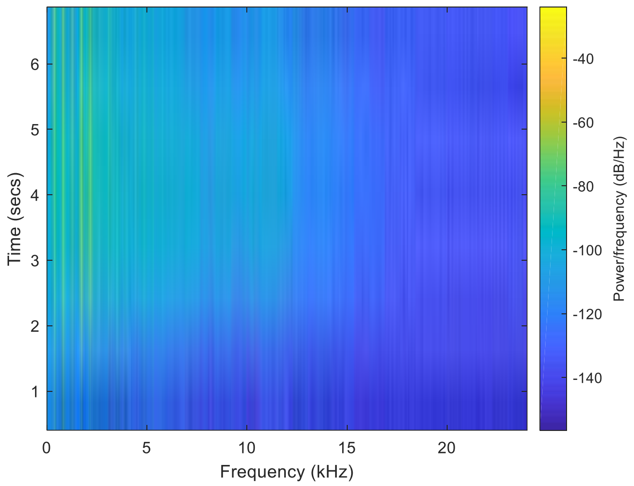

Figure 6 overlap= 38782

As we can see from the results from figure 5 and 6 we can understand that the smaller the overlap is the less we can see from the spectrogram.

Comparing nfft:

We can understand from the figure 7 and 8 that the larger the nfft is the less power we can see in the spectrogram result. As you can see in figure 7 the result is much brighter compared to the other one where it is pretty dark.

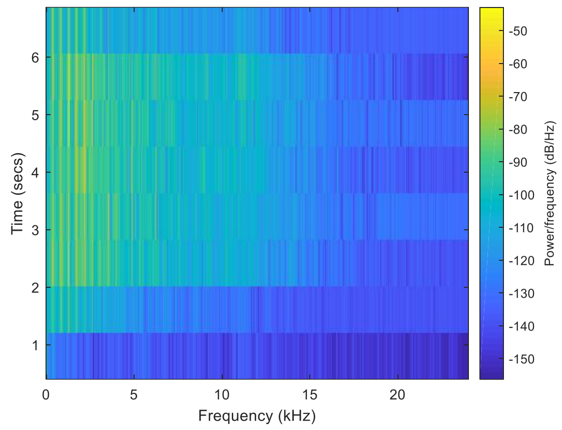

Figure 7 nfft=1000

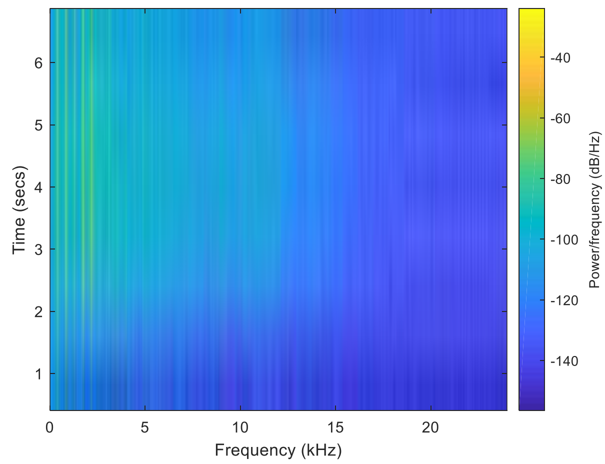

Figure 8 nfft= 524288

Pulse Rate Estimator

1) In this part we are going to plot the diagram of the heart pulse signal, and we are going to do that by measuring the frequency in the signals of the heart rate.

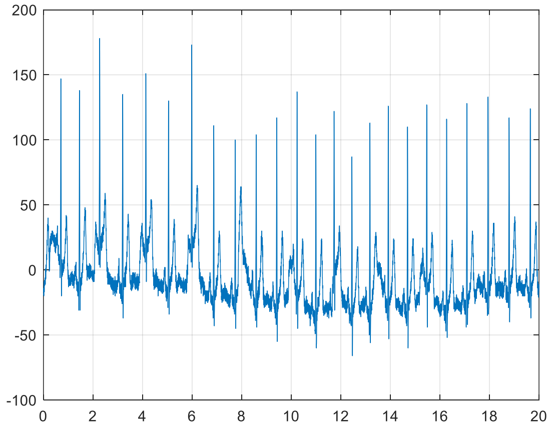

Figure 9 main signal

In figure 9 we can see the main image as we can notice it has a lot of noise that we must get rid of them.

2) According to this link a normal resting heart rate for adults ranges from 60 to 100 beats per minute. Generally, a lower heart rate at rest implies more efficient heart function and better cardiovascular fitness. For example, a well-trained athlete might have a normal resting heart rate closer to 40 beats per minute. As we can notice the frequency must be something near 1Hz.
3) In this part we are going to plot the frequency domain of the signal the result will look like figure 10.

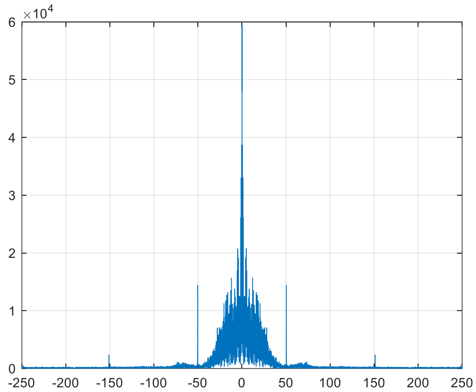

Figure 10

As we can see in figure 10 most of the power is around the 0 frequency domain and the are some peaks on 50Hz and 150Hz.

4) According to link the human's body muscles have frequency as well. The common frequencies of the artifact and noise on the ECG: Muscle: 5 – 50 Hz. Respiratory: 0.12 – 0.5 Hz (e.g. 8 – 30 bpm) External electrical: 50 or 60 Hz (A/C mains or line frequency). So this can be the proper reason for some on noises that we have the main source of them are the bodies movement.
5) In this part since we know the main heart beat has a frequency near 1Hz then are will use the two filters in order to eliminate the noise and we used the high-pass filter with 2Hz frequency and the loss-pass filter with the cute off frequency of 0.5Hz.

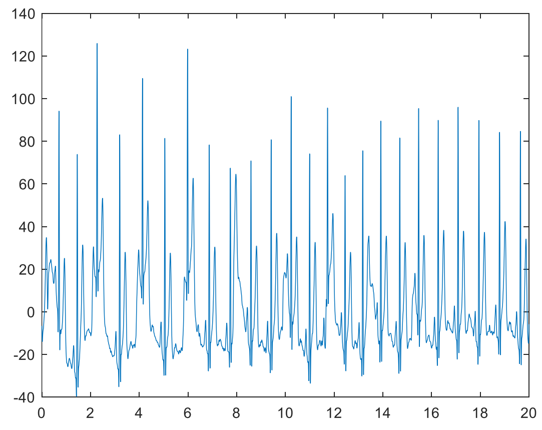

Figure 11

According to figure 11 we can notice that most of the noises are eliminated in the time so we use this in order to measure the frequency.

6) In this part we are going to show the result of the filtering and the output image we have in the end.

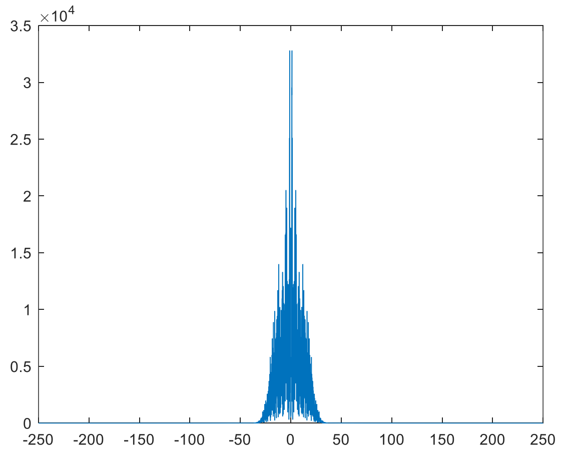

Figure 12

By using figure 12 we can find the maximum frequency magnitude and its value, for example for this one the result is 1.175Hz.

So with this technique we were able to measure the frequency of the heart signal.

Here is an image for this result.

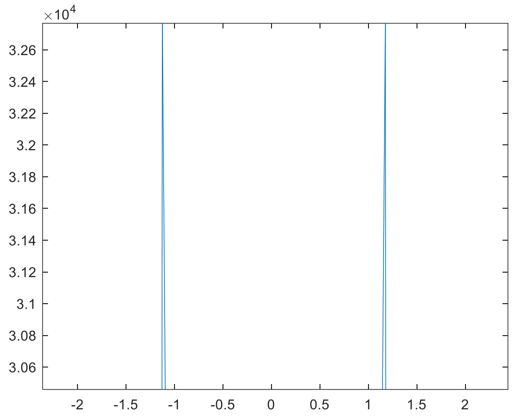

Figure 13

We can understand in the figure 13 that there are strong frequencies in 1.175Hz.

Data Imputation

1) In this part we downloaded the mentioned dataset and used pre-processing in order to make the data ready to use.
2) In this part we are going to record the heart rate for both sex and by recording these parameters we will plot the histogram for every single one of them.

In this part because the algorithm was not completely accurate we will get rid on the heart rates that are greater than 2 and smaller than 0.8 since we know what is the human normal range for heart beet and out of this range is not feasible so we got rid of them.

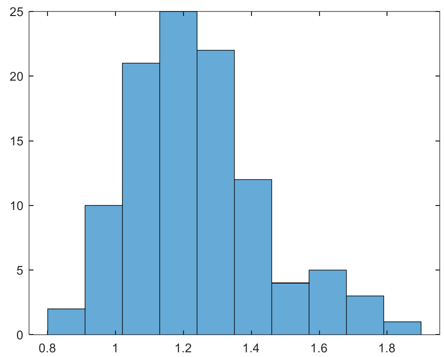

Figure 14 Male histogram

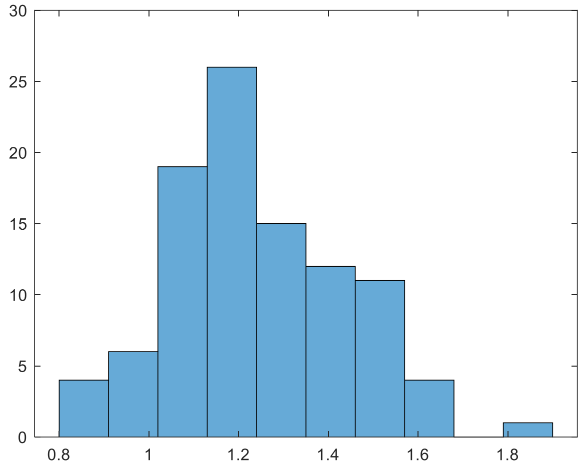

Figure 15 Female

As we can see in figure 14 the two distributions are very close to each other and it is hard and inaccurate to classify the sex base of the heart rate.

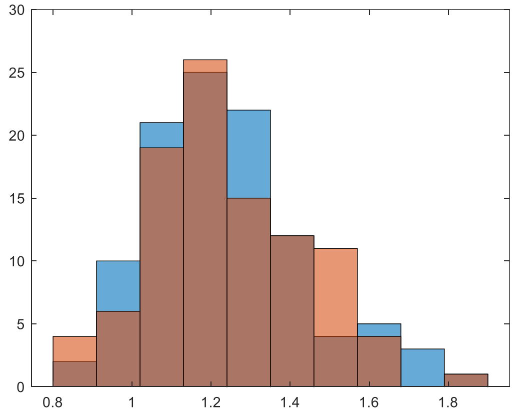

Figure 16 both sex

We can use figure 16 and show that there isn't much information to know about the histogram.

3) In this part we are going to record the heart rate and the age of every single sex and at the end we will plot the scatter plot of this and see with we can distribute.

According to figure 17 we can see the distribution of the two sex

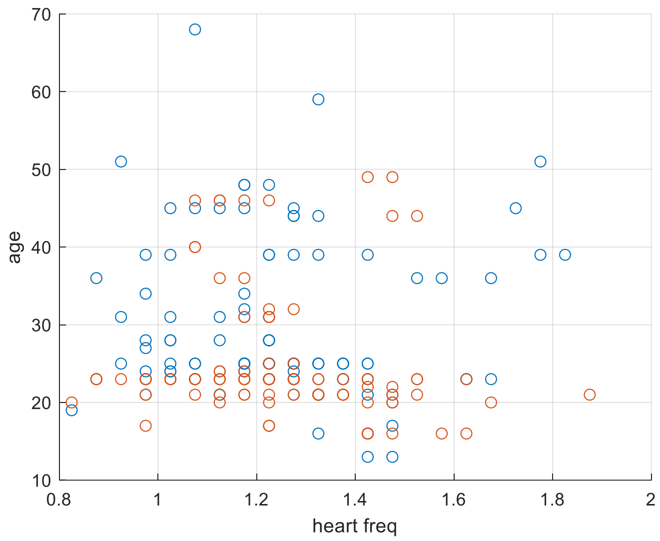

Figure 17

In figure 17 the blue spots are for male and the red are for female and we can see that it is easier to classify the sex by using this model since, the blue and red are both close to their own colors.