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Frequency Extraction of Phonocardiogram Signal using Fourier Transform

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Abstract

This article presents Fourier Transform application to extract features of Phonocardiogram Signals into its frequency components. Data was taken from Physionet Dataset of Phonocardiogram which comprises of normal and abnormal heart condition. Raw data was preprocessed using time clipping of 2 seconds at certain area that contains less noise. A lowpass filter was applied to denoise the raw signals. Experiments show the PCG of normal hearts has a dominant frequency of 50Hz to 150Hz, with the subdominant frequencies of 450 Hz to 650 Hz. The subdominant frequency of the normal hearts sometimes show anomaly with more amplitude compared to the dominant frequency.

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Abstrak

Artikel ini membahas penggunaan Transformasi Fourier untuk menganalisis sinyal Fonokardiogram (Phonocardiogram) dengan mengekstraksi komponennya dalam domain frekuensi. Data yang digunakan berasal dari Dataset Physionet Phonocardiogram, yang mencakup kondisi jantung normal dan abnormal. Data mentah diolah dengan memotong segmen berdurasi 2 detik pada area yang memiliki noise minimal. Untuk mengurangi gangguan, sinyal mentah difilter menggunakan lowpass filter. Hasil eksperimen menunjukkan bahwa PCG jantung normal memiliki frekuensi dominan di kisaran 50Hz hingga 150Hz, serta frekuensi subdominan di kisaran 450Hz hingga 650Hz. Pada beberapa kasus, frekuensi subdominan jantung normal menunjukkan anomali dengan amplitudo yang lebih tinggi dibandingkan frekuensi dominan.

1. INTRODUCTION

Phonocardiogram (PCG) signals record the acoustic vibrations produced by the heart activity. They are used for numerous purposes in clinical, as well as research contexts. One of the main uses in the diagnosis and monitoring of cardiovascular diseases (CVDs). PCG analsys helps detect abnormal heart conditions, such as valve disorders, arrythmias, and murmurs, which then related with structural and functional anomalies [1], [2], [3].

Besides diagnostics, PCG signals contribute to continuous health monitoring and personalized care. Implementation in the form of wearable devices enables real-time heart sound analysis, which then can be used to monitor the progress of chronic conditions and effectiveness of therapies. These applications are supported by the integration of PCG with other sources of information like Electrocardiogram (ECG). They provide a comprehensive view of one's cardiovascular health. The recent advancements in digital stethoscopes and data processing have also made PCG a practical tool in telemedicine and remote healthcare [4].

The phonocardiogram (PCG) signal provides a rich source of features for diagnosing and analyzing cardiac health. These features can be broadly categorized into time-domain, frequency-domain, and time-frequency domain characteristics. In the time domain, common features include heart sound intervals (S1 and S2 durations), systolic and diastolic durations, and inter-beat intervals. These features are essential

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for identifying abnormalities such as arrhythmias or valve issues [5]. Frequency-domain features, such as spectral energy, dominant frequency, and bandwidth, help in identifying murmur characteristics, often associated with turbulent blood flow caused by structural abnormalities in the heart. Time-frequency methods, like wavelet transform, enable the analysis of transient and non-stationary features, which are particularly useful for detecting subtle variations associated with murmurs and other dynamic heart conditions (e.g., ejection clicks or rubs) [1], [6].

The extraction and classification of these features are critical for automated diagnosis systems. Advanced techniques often combine multiple domains, such as using joint time-frequency representations, to enhance diagnostic accuracy. For example, machine learning models often use feature sets derived from these domains to classify PCG signals into normal or pathological categories. These features also facilitate identifying specific heart conditions, such as aortic stenosis or mitral regurgitation, by correlating signal characteristics with clinical presentations. Research continues to evolve, incorporating methods like deep learning and multi-modal data fusion (e.g., combining PCG with electrocardiograms) to improve diagnostic reliability and interpretability [7].

This PCG signal model can be analyzed using time domain analysis [2], [8], [9]. Another method used is frequency-domain analysis [10], [11]. Recent research on PCG analysis is combining these methods to have more accuracy [9], [10], [12] even using various methods of Machine Learning [6], [8], [9], [12].

2. METHODOLOGY

This section discusses several methods used in PCG signal analysis, including the model of PCG signal in time-domain, the Fourier Transform, and S-Transform. Fourier Transform is applied to perform frequency analysis, while S-Transform is used to show Power Spectrum.

2.1. Model of PCG signal

PCG signal model is shown in using two signals with low and different frequencies, with noise added as shown in (1) [13].

$$PCG(t) = A_1 \sin\big(\omega_1(t - t_1)\big) + A_2 \sin\big(\omega_2(t - t_2)\big) + noise(t) \quad (1)$$

This equation can be displayed Figure 1.

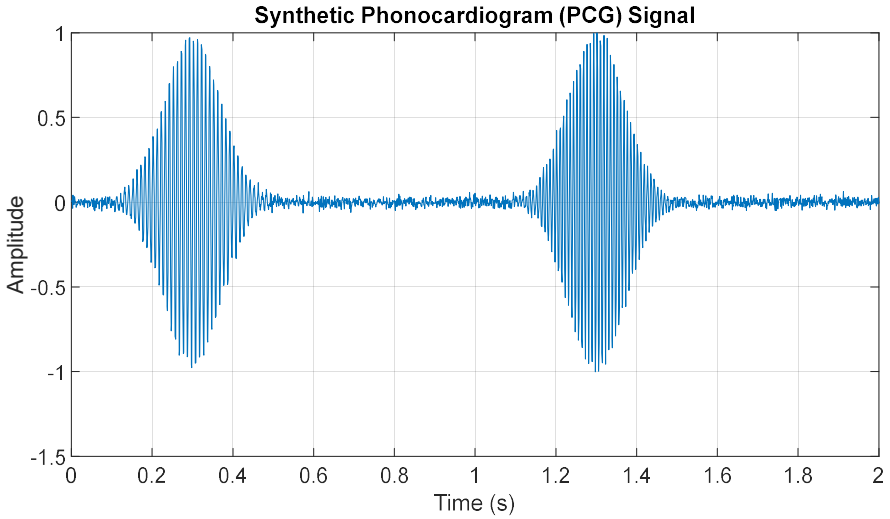

Figure 1. Model of Phonocardiogram Signal

2.2. Frequency Feature of PCG Signal

A PCG signal consists of five main frequency features, spectral roll off, median frequency, spectral centroid, dominant frequency, and spectral flux [14]. These features will then be used in further processing units [7], [14], [15] due to the properties shown in Table 1.

Table 1. Frequency properties of PCG Signals and their Significance.[14].

No.	Features	Maximum Percentage of (%)				
		Accuracy	Sensitivity	Specificity	PPV	NPV
1	Spectral roll-off	80.6	80.6	80.6	80.6	80.6
2	Median Frequency	87.4	87.7	90.0	87.2	87.6
3	Spectral Centroid	73.4	66.7	80.0	77.0	70.6
4	Dominant Frequency	73.6	66.5	80.6	77.4	70.7
5	Spectral Flux	71.8	65.9	77.7	74.7	69.5

2.3. Fourier Transform

The Discrete Fourier Transform (DFT) is a technique used to convert a finite sequence of equally spaced samples from the time domain into the frequency domain. It decomposes a signal into its constituent frequencies, which is critical in signal processing applications such as audio compression, wireless communications, and image processing. The DFT essentially projects the input signal onto a set of sinusoidal basis functions, enabling the analysis and manipulation of signal frequency content. Its computational efficiency was greatly enhanced by the development of the Fast Fourier Transform (FFT), which significantly reduces the complexity of computing the DFT [16], [17].

The DFT operates on finite-length signals, assuming periodicity within the analyzed sample, and provides a discrete representation of frequency components. This process makes it invaluable for digital signal processing tasks, including noise filtering, spectral analysis, and data compression. For example, in MP3 audio compression, the DFT identifies dominant frequency components in small blocks of data, enabling the efficient encoding of sound while maintaining audio fidelity. Additionally, the DFT is widely applied in scientific domains such as spectroscopy and MRI, where frequency-domain representations yield insights into underlying phenomena. Fourier transform is applied to breakdown signals to Frequencies components [16], [17]. To perform frequency analysis, first the PCG signals are calculated using Fourier series as shown in (2) as follows:

$$c_n = \frac{1}{p}\int_{-\frac{p}{2}}^{\frac{p}{2}} f(t)e^{-\left(\frac{2n\pi it}{p}\right)}dt, n \geq 0 \quad (2)$$

Fast Fourier Transform is applied to PCG signals as shown in Figure 2:

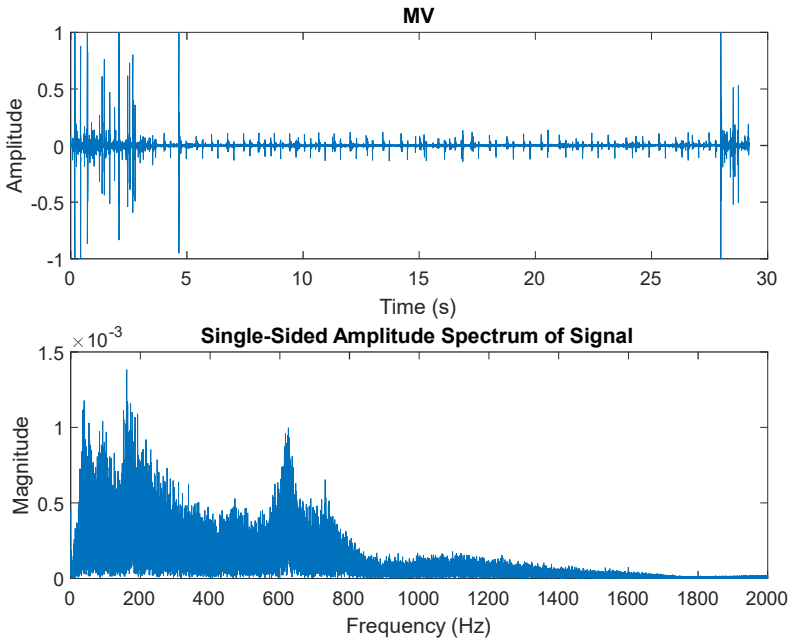

Figure 2. The application of Fourier Transform of a signal.

2.4. Preprocessing

PCG signals are extracted between time frame to denoised by bandpass filter to extract the frequency components of 20 Hz to 200 Hz [18]. The next step is applying wavelet transform to attenuate high frequency [2], [19] and followed by detect high-energy S1 and S2 [20]. The final stage of preprocessing is normalization to bring all signals to the same level [21].

3. RESULT AND DISCUSSION

There are two types of labels used in this work, Normal and Abnormal. Ten samples of each label are randomly taken from Physionet Data. These samples are then pre-processed

Table 2. Random samples from PCG dataset.

No.	Idx	Sample number	Label	No.	Idx	Sample number	Label
1	758	85161	Abnormal	11	722	85099	Normal
2	373	50826	Abnormal	12	91	49974	Normal
3	601	84853	Abnormal	13	235	50311	Normal
4	127	50056	Abnormal	14	99	49990	Normal
5	379	57706	Abnormal	15	674	85000	Normal
6	232	50300	Abnormal	16	373	50094	Normal
7	451	68698	Abnormal	17	639	84933	Normal
8	8	29378	Abnormal	18	577	84798	Normal
9	28	49562	Abnormal	19	103	49998	Normal
10	10	33151	Abnormal	20	431	68470	Normal

The PCG signal of sample number 674 in time domain is shown in

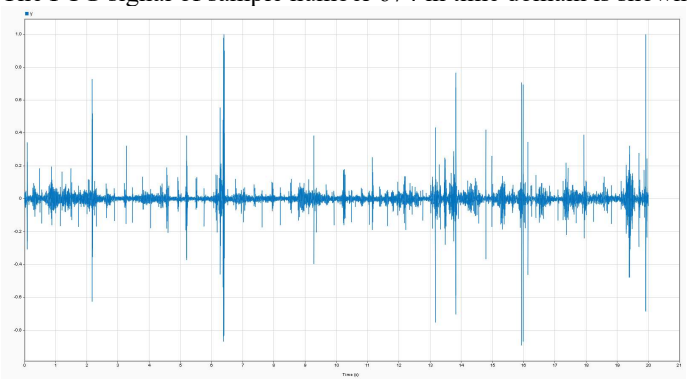

Figure **3**.

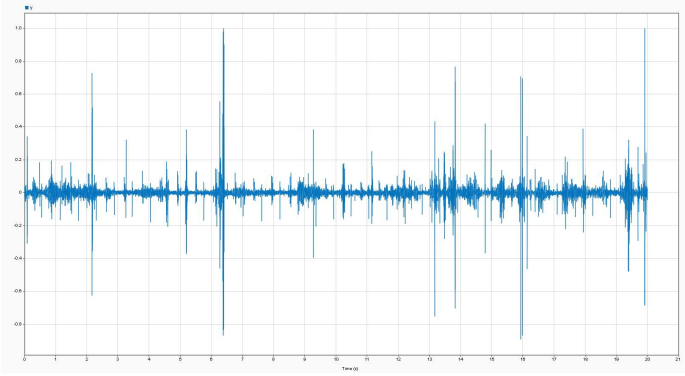

Figure 3. Raw PCG signal of sample number 674 in time domain.

In the frequency domain, this signal is shown in Figure 4.

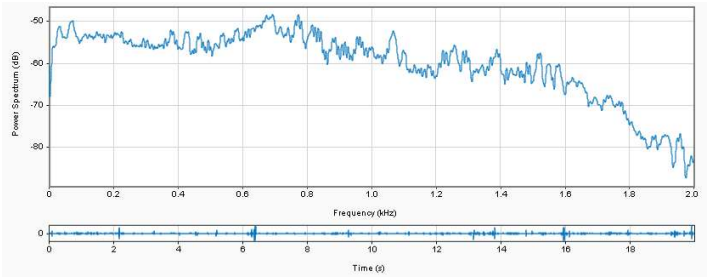

Figure 4. Raw PCG signal of sample number 674 in frequency domain.

Figure 3 and Figure 4 show that the raw PCG signal is noisy and thus, is not ready for further processings. In the time domain, some areas show spikes that will decimate others when normalized. This causes the distribution of frequency to be indistinguishable. The next step is to determine the Region of Interest RoI to address the problem. The result of this step is shown in Figure 5 while the frequency domain of the RoI is shown in Figure 6.

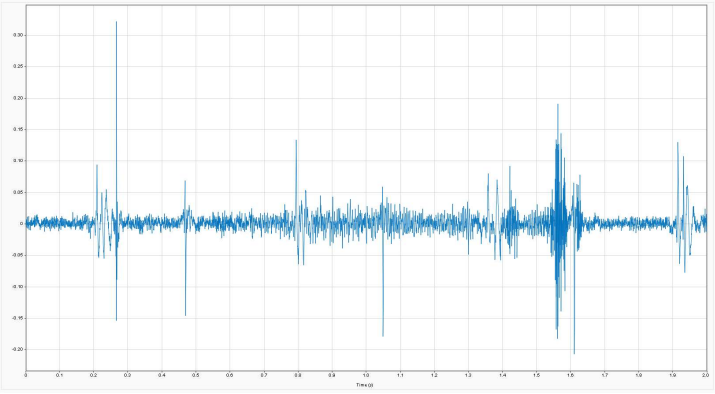

Figure 5. PCG signal of sample number 674 RoI in time domain.

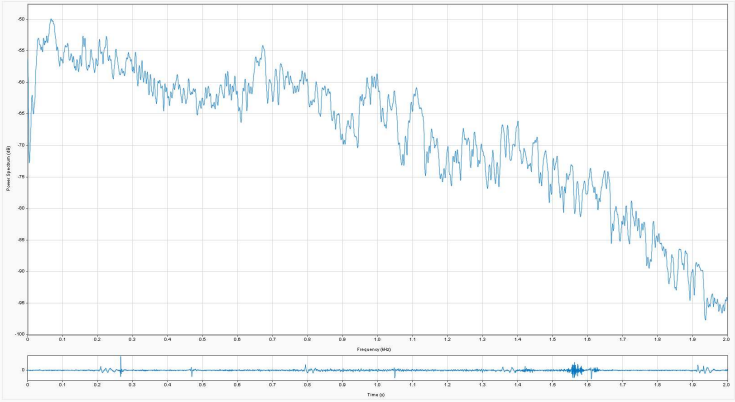

Figure 6. PCG signal of sample number 674 RoI in frequency domain.

Compared to the raw signal, the RoI signal shows more distinguishable features. In time domain, S1 and S2 are more obvious than the raw signal, while in the frequency domain, the frequency of 0 to 100 Hz is dominant compared to higher frequencies. There is also a dominant frequency range between 600 Hz to 700 Hz as shown in Figure 7.

On the other hand, PCG signal of normal heart comprises of less noise in time domain, while in the frequency domain, the dominant frequencies remain the same with more dishtinguishable compared to the rest, as shown in and Figure 8.

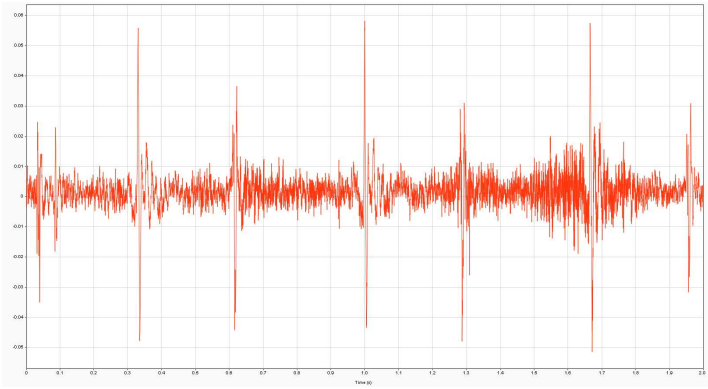

Figure 7. PCG signal of sample number 674 RoI in frequency domain.

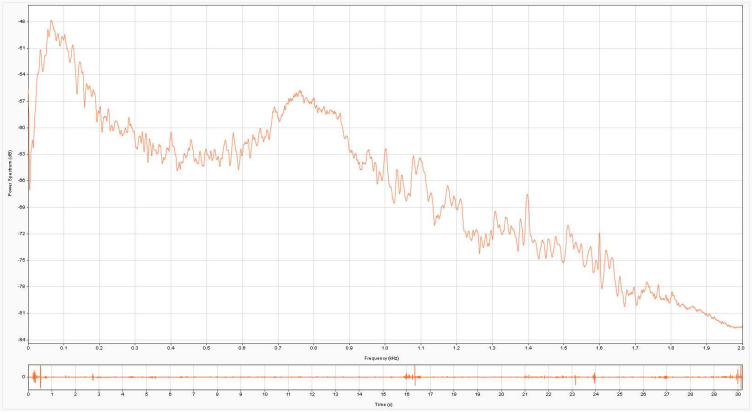

Figure 8. Raw PCG signal of sample number 373 in frequency domain.

Clipping the signal resulting distinguish S1 and S2 with considerable noise, as shown in Figure 9. In frequency domain, the frequency 0 Hz to 100 Hz is still dominant, while the frequency 600 Hz to 700 Hz is slightly more than the remaining frequencies, as shown in Figure 10.

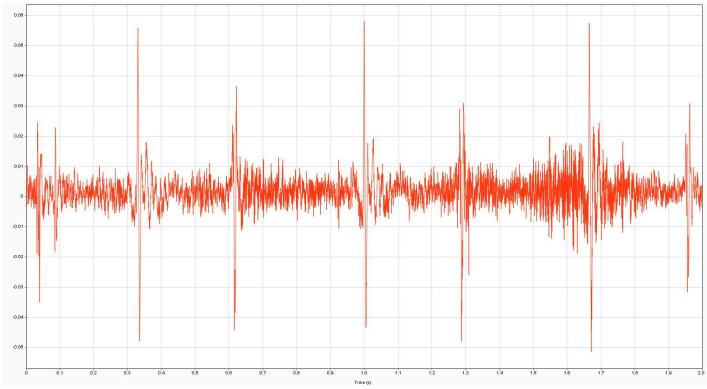

Figure 9. RoI of PCG signal of sample number 373 in time domain.

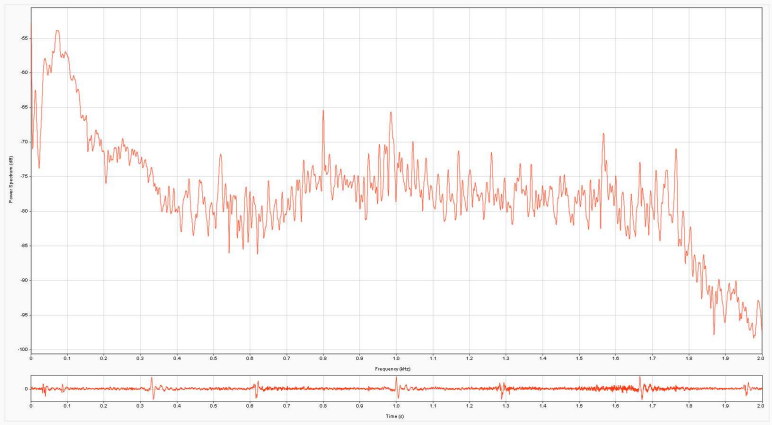

Figure 10. RoI of PCG signal of sample number 373 in frequency domain.

Applying a low pass filter with the cut-off frequency of 150 Hz and gradient 0.85 does not make significant change in time domain. In the frequency domain however, the frequency component of the higher frequencies attenuated significantly as shown in Figure 11.

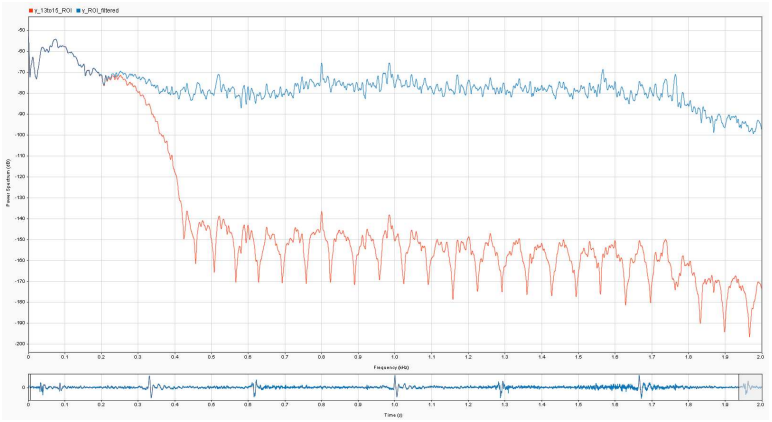

Figure 11. Normal and filtered PCG signal comparison of sample number 373 in frequency domain.

4. CONCLUSION

This paper performs frequency analysis of random samples of PCG signal taken from Physionet dataset. Samples comprises of random ten samples each of normal and abnormal heart conditions. Sample number 674 is a normal heart with the feature of more order in heartbeat and the dominant frequency between 50 Hz to 150 Hz. In some samples it is found that the signal with subdominant frequencies have higher amplitude than the dominant frequencies itself.

The signals of normal heart conditions sometimes have more frequencies spread across the frequency domain. It is found that subdominant frequencies have features, which in future can be explored to find more correlations between some tima and frequency features of the PCG signals [19], [22], [23].

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