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COMPARISON OF MULTISCALE FREQUENCY CHARACTERISTICS OF NORMAL PHONOCARDIOGRAM WITH DISEASED HEART STATES

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ABSTRACT

Phonocardiogram (PCG) signals are electrical recording of heart sounds containing vital information of diagnostic importance. Several signal processing methods exist to characterize PCG, however suffers in terms of sensitivity and specificity in accurately discriminating normal and abnormal heart sounds. Recently, a multiscale frequency (MSF) analysis of normal PCG was reported to characterize subtle frequency content changes in PCG which can aid in differentiating normal and abnormal heart sounds. In this work, it was hypothesized that MSF can discriminate normal PCG signal compared to an artifact, PCG with extra systolic heart sounds and murmur based on their varying frequency content. Various samples of PCG with normal and abnormal heart sounds were obtained from Peter Bentley Heart Sounds Database sampled at 44.1 kHz for analysis. The signal was filtered using a 4th order Butterworth lowpass filter with cutoff frequency at 200 Hz to remove higher frequency noise and MSF estimation was performed on the filtered dataset using custom MATLAB software. Mann-Whitney test was performed for statistical significance at $p < 0.05$. Results indicate that MSF successfully discriminated normal and abnormal heart sounds, which can aid in PCG classification with more sophisticated analysis. Validation of this technique with larger dataset is required.

Keywords: phonocardiogram, PCG, multiscale frequency, heart sound, cardiac disease.

1. INTRODUCTION

Cardiovascular diseases are the leading cause of death worldwide despite significant advancement in science and technology affecting several million people annually [1]. Depending on the specific biomedical signal and methods used for cardiac disease prognosis and diagnosis, several challenges currently exist for accurate profiling variety of diseases due to the sensitivity and specificity of the methods used. The most common cardiac signal is the ECG, analysis of which has proven significant success in detecting numerous heart diseases using complex analysis techniques [2-6] which are also useful in real-time monitoring. Similarly phonocardiogram (PCG)

signals i.e. heart sounds which are discrete bursts of auditory vibrations of varying Intensity (loudness), frequency (pitch), quality and duration are analyzed for diagnosing variety of heart diseases [7]. Two prominent but different sounds namely S1 and S2 are normally generated by the closing of atrioventricular valves and semilunar valves during each cardiac cycle. A third heart sound which is of low intensity namely S3 is produced due to the opening of mitral valve .The fourth heart sound or S4 is generally not audible but it can be audible in case of more rigid ventricles [8]. It has been reported that S1 has duration of about 0.15s and the frequency ranges from 25-45 Hz. S2 has duration of about 0.12s and ranges from 50-200Hz frequency [7]. Studies have reported the frequency range of spectrogram [9] in PCG between 4-200Hz with a maximum limit up to 500 Hz. In case of heart valve problem the frequency range becomes greater than 1000Hz especially for the murmur [1, 11] condition of the heart. Various heart valve problems [7] can be detected by analyzing the PCG waveform and its spectrogram.

Many different methods on PCG analysis have focused on accurately segmenting S1 and S2 sounds and further classify different disease states. Several such techniques include cepstral analysis, frequency analysis by z-chirp transform (CZT) algorithm, homomorphic filtering and K-means clustering, wavelet transform, neural networks, support vector machine (SVM) and many other machine learning methods [10-14]. Although, these methods offers promise in reliable classification of heart sounds and disease classification, these methods are still limited by performance when presented with noisy and challenging PCG data from the digital acquisition.

Recently, we proposed the use of a multiscale frequency (MSF) [15-17] approach that takes into account the contribution from various frequencies in PCG to yield valuable information regarding the instantaneous frequency state of the PCG. MSF technique was shown to successfully identify the pivot point of rotors (electrical sources of cardiac activation) using noise-free optical mapping data in isolated rabbit heart [16-19], discriminate single lead ECG from normal sinus rhythm and atrial fibrillation [20-21] and sleep apnea [22] with short time series analysis. The results were promising that opened new avenues of applications for the MSF technique including PCG analysis. The purpose of this study was to build upon our previous work on characterizing PCG signals of different pathological conditions using MSF and compare it with normal PCG that can aid in highly reliable PCG classification..

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2. MATERIALS AND METHODS

A. Multiscale Frequency Technique

A wide range of local MSF estimate [15] can be obtained by weighted summation over the eight different filter pairs as previously described using the following equation 1:

$$MSF = \rho_o \left[\sum_{i=1}^{N-1} q_i \right]^{-1} \sum_{i=1}^{N-1} 2^{i+0.5}\, q_{i+1} \qquad (1)$$

MSF can be used for complexity analysis for any non-linear, non-stationary short and long time series data. Fig. 1 shows a simplified block diagram of the MSF technique. Input biomedical time series is filtered through the filter bank cascade and MSF index is obtained as the average value across the time series.

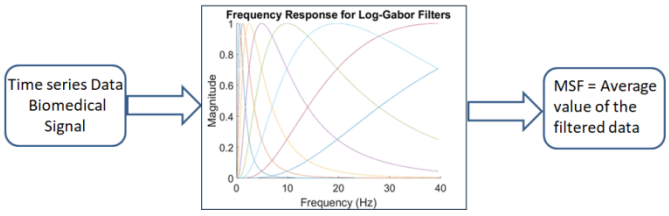

Fig. 1: Block diagram illustrating MSF technique

B. Peter Bentley Heart Sounds Database

Publically available PCG datasets were used from the Peter Bentley Heart Sounds Database [23]. 19 samples of normal PCG, artifact and extra systolic heart sound signal and 13 samples of murmur PCG were obtained for analysis which was sampled at 44.1 kHz. A 4th order Butterworth lowpass filter was designed with cutoff frequency at 200 Hz to remove higher frequency noise and MSF estimation was performed on the filtered PCG dataset as described above to profile the multiscale frequency state of the normal PCG signal using custom MATLAB software. Statistical significance test was performed using Mann-Whitney test using OriginPro software with p value less than 0.05 considered as statistically significant.

3. RESULTS AND DISCUSSION

Fig. 2 (top) shows a representative example of a normal PCG signal and (bottom) shows the normalized power spectrum of the signal, while Fig. 3 show the low pass filtered signal. Figs. 4 & 5 show the synthetic artifact sound signal and its spectrum in its raw and filtered form respectively. As seen from Figs. 2 & 3, normal PCG has prominent frequencies till 200 Hz, while the while the artifact signal constituted wide range of frequencies over 500 Hz, and was filtered at 200 Hz cut off as seen in Figs. 4 & 5 respectively. Figs. 6 & 7 show the raw and filtered spectrum of the extra systolic heart sound displaying frequency characteristics slightly different than normal PCG. Figs. 8 & 9 show the raw and filtered signal spectrum of murmur signal. As seen from Fig. 8, murmur PCG constituted narrow range of frequencies within 150 Hz. This data was seen to be in contrary to what was expected as the frequencies were well within 200 Hz range as compared to 1000 Hz range [11] for heart murmur. Murmur was clearly

noted in the PCG denoted by marked signals between consecutive cardiac cycles from the time series plots in Figs. 8 & 9. Marked difference is seen in the spectrum of normal PCG and murmur PCG, with higher frequency content in normal PCG than in murmur indicating the possibility of higher MSF for normal PCG than murmur, which was expected otherwise.

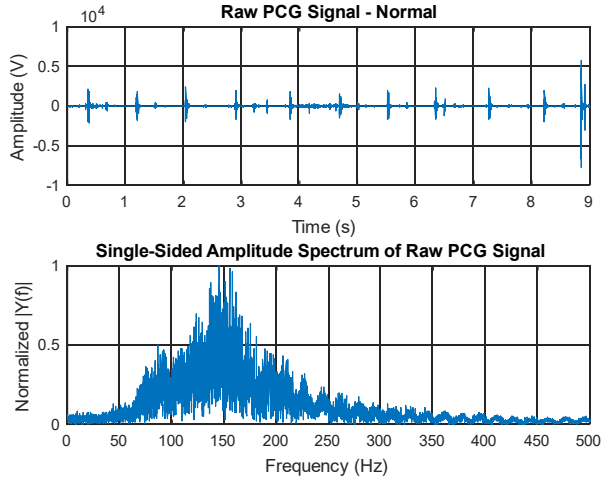

Fig. 2: (Top) Plot of a raw normal PCG signal; (Bottom) Normalized power spectrum of the normal raw PCG signal.

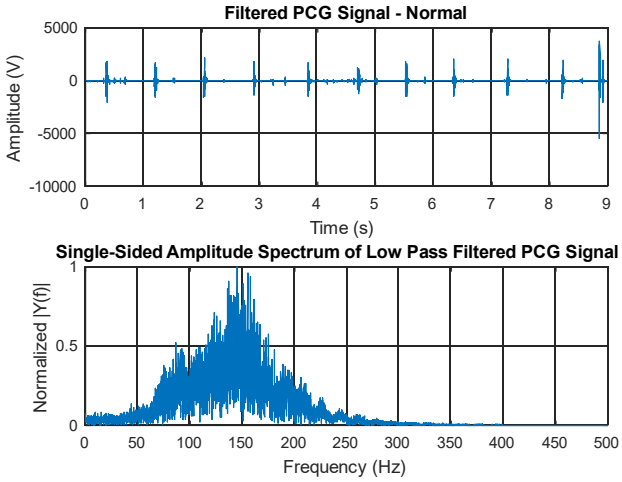

Fig. 3: (Top) Plot of a low pass filtered normal PCG signal; (Bottom) Normalized power spectrum of the low pass filtered PCG signal.

The mean MSF of the normal PCG was 91.88±29.75 Hz; The mean MSF of the extra heart sound signal was 111.44±26.36 Hz. The mean MSF of the artifact sound signal was 112.66±18.63 Hz; and the mean MSF of the murmur sound signal was 47.71±16.31 Hz. Normal PCG and murmur sound signals were statistically different on MSF with $p < 0.05$ similarly normal PCG was different on MSF compared to the artifact and extra systolic heart sound signal with statistical significance $p < 0.05$. Fig. 10 shows the boxplot of the MSF values for the normal PCG signal, artifact, extra heart sound and the murmur sound signal. As seen from the figure, since artifact signal was synthetic much of the made up frequencies matched with the frequencies of the extra heart sound.

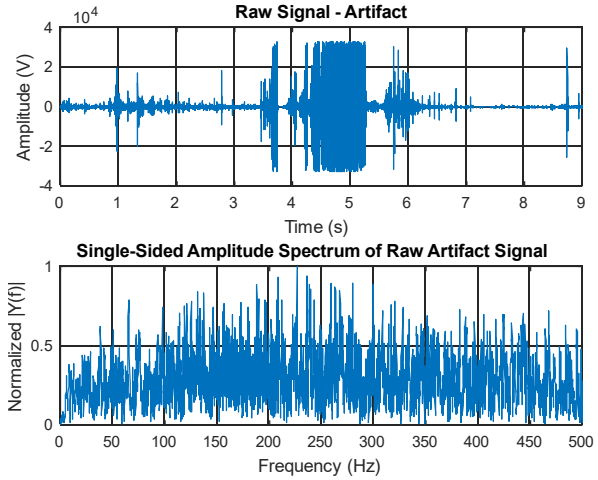

Fig. 4: (Top) Plot of a raw artifact sound signal; (Bottom) Normalized power spectrum of the artifact sound signal

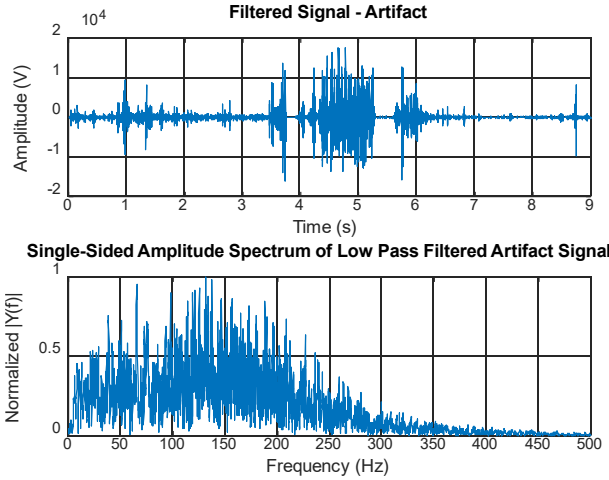

Fig. 5: (Top) Plot of filtered artifact sound signal; (Bottom) Normalized power spectrum of the filtered artifact sound signal

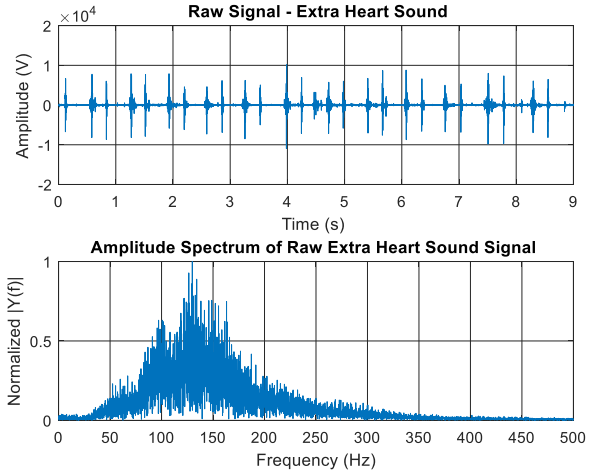

Fig. 6: (Top) Plot of PCG signal with extra heart sound; (Bottom) Normalized power spectrum of the PCG signal with extra heart sound

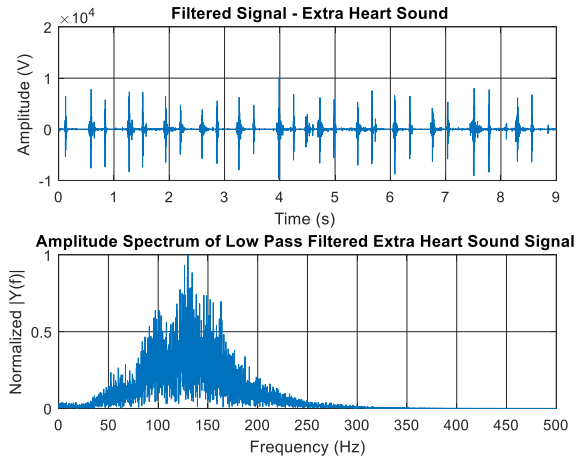

Fig. 7. (Top) Plot of filtered PCG signal with extra heart sound; (Bottom) Normalized power spectrum of the PCG signal with extra heart sound

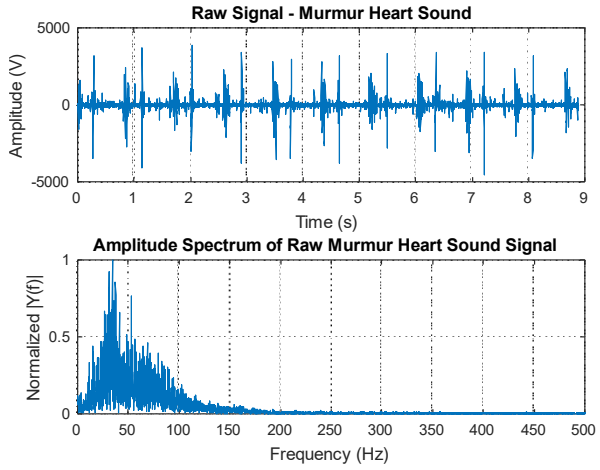

Fig. 8 (Top) Plot of a raw PCG signal with murmur; (Bottom) Normalized power spectrum of the raw PCG signal with murmur.

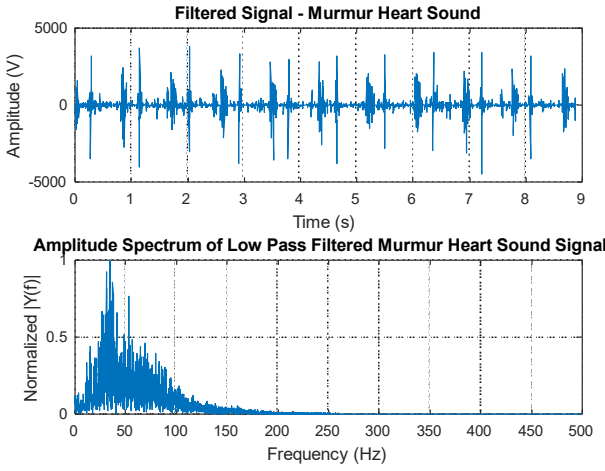

Fig. 9: (Top) Plot of a filtered PCG signal with murmur; (Bottom) Normalized power spectrum of the filtered PCG signal with murmur.

Because of the overlapping frequencies in extra heart sound and the artifact, MSF was not different between these two signals. However, MSG was significantly different between extra heart sound and murmur signal. Murmur signal had a significantly lower MSF compared to the extra heart sound. These, results offer great potential in discriminating and classifying PCG's based on their frequency content that can aid in a variety of cardiac diseases non-invasively.

In this work, PCG signals were characterized using multiscale frequency analysis, a perspective that is novel to the biomedical signal processing domain as a variation of the instantaneous frequency. High variability among normal PCG was observed with a standard deviation of 29.75 Hz, the differences could be attributed to the acquisition of the PCG using the digital stethoscope, which often is a challenge. The results suggest more accurate digital PCG collection with reliable hardware and acquisition approach. The murmur PCG signal clearly showed the murmur activity, however contained frequencies that ranged lower compared to normal PCG which was captured by the MSF algorithm yielding lower MSF values for murmur compared to normal PCG demonstrating statistical significance. MSF accurately picked up the frequency changes in the extra heart sound signal in reliably discriminating from other PCG's.

In this work a novel perspective of the PCG signal was presented based on the multiscale frequency content. Since the S1 and S2 sounds have unique frequency bands, a pathological state of the heart can result in altered frequency bands that can result in different instantaneous frequency that can be tapped for accurate and reliable diagnosis of the disease. Therefore, the murmur caused from the pathological state of the valves altered the natural frequency content of the PCG, with lower contributing frequencies in this case, resulting in lower MSG compared to normal PCG. Similarly, the extra beat introduced several other frequencies that increased the MSF naturally. This approach did not use sound classification i.e. s1 or s2 which many methods use, rather profiling the total instantaneous frequency content which varies depending on the heart condition such as normal or pathology. The preliminary results presented in this work demonstrated robust classification with minimal samples; however the findings need further validation with larger number of datasets.

Cleaner PCG dataset is desired that can result in accurate multiscale profiling of the PCG signal that can yield in more reliable discrimination with higher sensitivity and specificity. The results are promising to accurately discriminate normal PCG's between pathological conditions such as extra heart sound and murmur based on MSF which motivate the use of this MSF technique for variety of other PCG signal analysis as a step towards integrating into a wearable PCG device. Future work will focus on validation with larger normal dataset and also exploring several other diseased cardiac conditions.

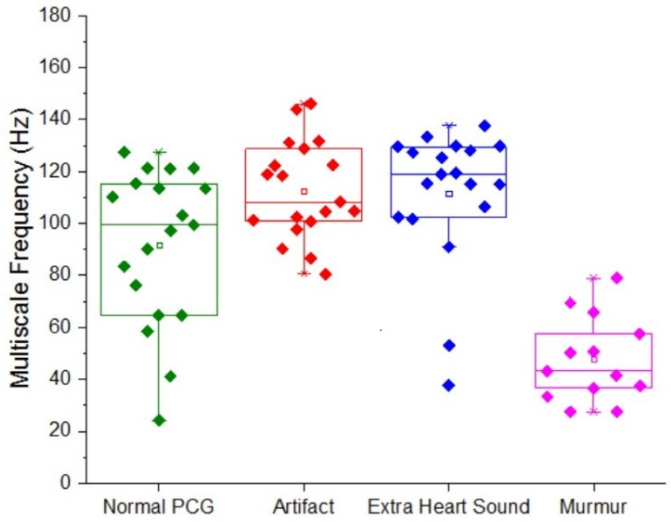

Fig. 10: Boxplot of MSF values for the normal PCG, artifact sound signal, extra heart sound,= and murmur signals. MSF can discriminate between extra heart sound and murmur compared to normal PCG.

4. CONCLUSION

In this work, multiscale frequency content of PCG has been explored and results show that MSF technique can discriminate normal from abnormal heart sound such as extra heart sound and murmur robustly. With preventive medicine the future scope of healthcare, emerging new and smart devices for real-time ECG/PCG monitoring could potentially use MSF approach for complexity analysis for prognosis and diagnosis of variety of cardiac conditions, with respect to preventive cardiology. Robust and efficient adaptive filter bank design could significantly improve the complexity analysis of PCG and other biomedical signals in an adaptive fashion.

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