Phonocardiography Data Compression using Discrete Wavelet Transform

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Telemedicine and other remote early intervention techniques play a vital role to improve the cardiac patient survival rate and decrease their hospitalized rate. Phonocardiography (PCG) is a widely used diagnostic tool to quickly identify the heart condition. It provides supplement diagnostic information to Electrocardiogram (ECG) as it can detect the structural defects of the heart that ECG cannot identify. Therefore, continuous PCG monitoring is of great interests for remote patient monitoring [1] [2]. However, 24 hours online monitoring generates a large amount of data to be transferred and stored at healthcare facilities. Moreover, end-to-end encryption is also required to share the data without compromising privacy or security. So, the data compression and encryption are necessary for the continuous monitoring of the PCG signal. But, very little research has been done on the compression of the PCG signal and the compression of the ECG signal is widely studied. This paper describes a PCG signal compression and encryption method which is suitable for the wireless cardiac patient monitoring applications.

The aim of an efficient data compression process is to remove all the redundant information from the signal without losing any data containing pathological information. We can achieve the compression by reducing the number of samples required to store and to transfer the PCG signal, thus it will reduce the memory space and the bandwidth requirements. Popular compression techniques include Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Discrete Sine Transform (DST) and Discrete Wavelet Transform (DWT). Among these methods, DWT performs better for the compression of the non-stationary signal like PCG due to its multi-resolution analysis feature [3] [4]. This paper presents an intelligent algorithm to compress the PCG signal using DWT. First, we decomposed the original signal into multi-resolution sub-bands. Then we used an adaptive thresholding method based on the energy compaction property of the wavelet coefficients of each sub-band to compress the signal without distortion [5]-[10]. The compression algorithm is validated by testing on the large sets of normal and abnormal PCG signals available in the University of Michigan heart sound and murmur library [11]. We evaluated the performance of the algorithm by using compression ratio (CR), percentage of compression (PC), and percent root mean square difference (PRD). The objective of any compression technique is to achieve maximum CR and PC by preserving the features of signal with minimum PRD.

The selection of the best mother wavelet is crucial for the reconstruction of the compressed signal. To evaluate the performance of the best mother wavelet, we carried an extensive simulation among 20 wavelets from Daubechies family, 5 wavelets from Coiflets family and 15 wavelets from both Biorthogonal and Reverse-Biorthogonal families (total 55 orthogonal wavelets). Among all of these wavelets db18 wavelet is chosen from Daubechies family as it outperformed all the other wavelets by giving the best compression performance and by maintaining the fidelity of the compressed signal with respect to the original signal [12]. All the PCG signals in the database are compressed at about 93.67% with an average CR of 15.85 and an average PRD of < 0.50%. The performance of this method is compared with 21 ECG compression techniques presented in the review paper [13]. The CR of those compression methods ranges from 2.0 to 23.1 and a range of the PRD from 0.61% to 28% has been reported.

Furthermore, to ensure the secure transmission of the signal, we developed an encryption procedure by using run-length encoding (RLE) and run-length decoding (RLD), so that only the receiver can decode the signal [14]. The qualitative design and the analysis of this compression technique could also be used on other remote patient monitoring data management.

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Abstract

Telemedicine and other remote early intervention techniques play a vital role to improve the cardiac patient survival rate and decrease their hospitalized rate. Phonocardiography (PCG) is a widely used diagnostic tool to quickly identify the heart condition. It provides supplement diagnostic information to Electrocardiogram (ECG) as it can detect the structural defects of the heart that ECG cannot identify. 24 hours online monitoring generates a large amount of data to be transferred and stored in healthcare facilities. Moreover, end-to-end encryption is also required to share the data without compromising the privacy or security. So, the data compression and encryption are necessary for the continuous monitoring of the PCG signal.

We compressed and encrypted the PCG signal using the following techniques:

- Discrete Wavelet Transform (DWT) is used for the compression of the PCG signal due to its multi-resolution analysis feature.
- Decomposed the original signal into multi-resolution sub-bands.
- Applied an adaptive thresholding method based on the energy compaction property of the wavelet coefficients of each sub-band to compress the signal without distortion.
- Encrypted the signal using Run-Length Encoding (RLE) .
- Reconstructed the signal using Run Length Decoding (RLD) and Inverse Discrete Wavelet Transform (IDWT).
- 55 different mother wavelets were compared to choose the best mother wavelet.
- The compression and encryption algorithm is validated by testing on the large sets of normal and abnormal PCG signals available in the University of Michigan heart sound and murmur library.
- Evaluated the performance of the algorithm by using compression ratio (CR), percentage of compression (PC), and percent root mean square difference (PRD).
- All the PCG signals in the database are compressed at about 93.67% with an average CR of 15.85 and an average PRD of < 0.50%.
- The performance of this method is compared with 21 ECG compression techniques.
- The CR of those compression methods ranges from 2 to 23.1 and a range of the PRD from 0.61% to 28% has been reported.

Materials and Methods

Signal Decomposition (By applying Discrete Wavelet Transform) → Thresholding (By applying Energy Packing Efficiency) → Signal Compression and Encryption (By applying Run Length Encoding) → Signal Reconstruction and Decryption (By applying Run Length Decoding and Inverse Discrete Wavelet Transform)

Figure.1: Block diagram of the compression and encryption algorithm

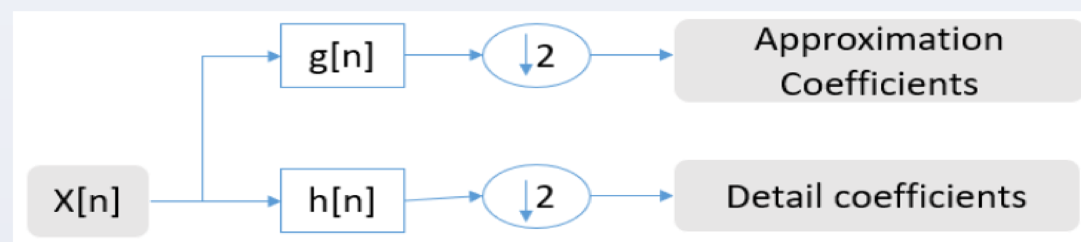

Figure 2: A Discrete wavelet transform model of 1 level decomposition

Energy Packing Efficiency (EPE)

$$EPE_i(\%) = \frac{\sum_{n=1}^{k_i}(c(n)^2)}{\sum_{n=1}^{k}(c(n)^2)} \times 100$$

Where n is an integer, k_i is the number of DWT coefficients in the ith sub-band and k is the number of all the DWT coefficients.

Table 2: Performance analysis of 14 different mother wavelets

Wavelets	PRD (%)	Approximation Band Energy (%)	Wavelets	PRD (%)	Approximation Band Energy (%)
db1	10.5011	95.6588	bior2.2	0.5949	99.8650
db3	0.4303	99.9243	bior3.7	0.1003	99.9880
db11	0.0676	99.9935	bior4.4	0.1458	99.9813
db18	**0.0613**	**99.9964**	rbio2.2	5.0183	98.8315
db20	0.0651	99.9944	rbio3.7	0.2036	99.9423
coif1	1.5591	99.6369	rbio4.4	0.3055	99.9389
coif3	0.0959	99.9845	rbio6.8	0.0924	99.9829

Table 3: Energy packing efficiency of different sub-bands

Sub-band	Energy	Value of EPE (%)	Coefficients
Approximation Band (A6)	6259.3340	99.9964	3135
Details Band (D6)	0.2257	3.605×10^{-05}	3135
Details Band (D5)	0.0024	3.689×10^{-07}	6235
Details Band (D4)	1.7669×10^{-05}	2.823×10^{-09}	12435
Details Band (D3)	5.9396×10^{-06}	9.489×10^{-10}	24836
Details Band (D2)	9.6516×10^{-06}	1.542×10^{-09}	49638
Details Band (D1)	1.5877×10^{-05}	2.5365×10^{-09}	99242

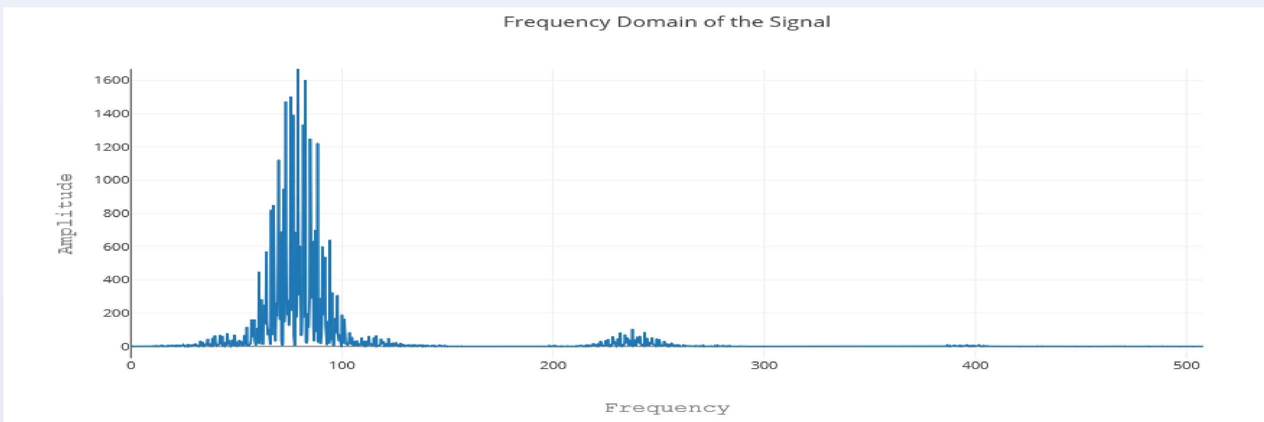

Figure 3: Frequency spectrum of the PCG Signal (Record-14)

Table.1:Different levels and their coefficients and frequency spectrum

Levels	Frequency range	Coefficients	Name of the sub band
6	0 to 344.531	3135	Approximation Band (A_6)
6	344.531 to 689.025	3135	Detail Band (D_6)
5	689.0625 to 1378.125	6235	Detail Band (D_5)
4	1378.125 to 2756.25	12435	Detail Band (D_4)
3	2756.25 to 5512.5	24836	Detail Band (D_3)
2	5512.5 to 11025	49638	Detail Band (D_2)
1	11025 to 22050	99242	Detail Band (D_1)

Table 4: Significant and zero coefficients before and after thresholding

	Total Coefficients	Significant Coefficients	Zero coefficients
Before Thresholding	198656	197401	1285
After Thresholding	198656	6236	192420

Original Data

1	1	1	1	1	1	0	0	2	2	2	2	2	2	2	2	2	0	0	0	0

RLE Representation

6	1	2	0	9	2	4	0

Figure 4: Run-Length Encoding

Results

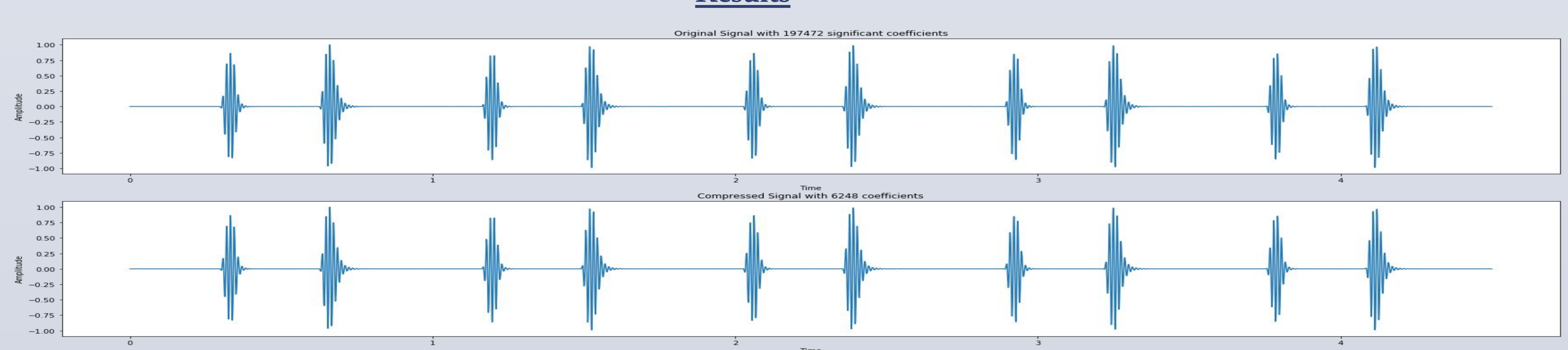

Figure.5: a) Original PCG signal (Record-14) b) Compressed PCG Signal (Record-14)

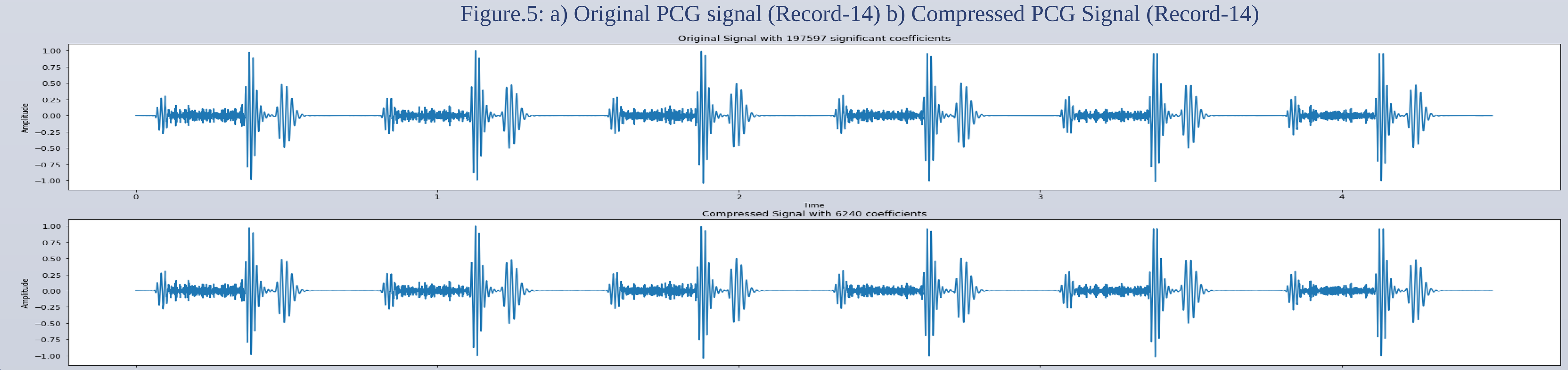

Figure 6: a) Original PCG signal (Record-12) b) Compressed PCG Signal (Record-12).

Table 5: Threshold, CR, PC and PRD of different records of the database

Record	Threshold	CR	PC (%)	PRD (%)
1	0.126	15.80	93.66	0.038
2	0.111	15.86	93.68	0.075
3	0.154	15.86	93.68	0.084
4	0.108	15.86	93.68	0.077
5	0.084	16.02	93.76	0.040
6	0.072	15.86	93.68	0.091
7	1.162	15.86	93.68	1.115
8	0.509	15.86	93.68	0.495
9	1.027	15.86	93.68	0.747
10	0.246	15.86	93.68	0.310
11	0.540	15.86	93.68	0.677
12	0.815	15.86	93.68	0.825

Table 6: Threshold, CR, PC and PRD of different records of the database

Record	Threshold	CR	PC (%)	PRD (%)
13	0.096	15.79	93.66	0.434
14	0.061	15.87	93.69	0.061
15	0.189	15.85	93.68	0.154
16	0.118	15.85	93.68	0.161
17	0.235	15.85	93.68	0.602
18	0.064	15.85	93.68	0.061
19	0.103	15.85	93.68	0.071
20	0.080	15.85	93.68	0.066
21	0.143	15.80	93.66	0.605
22	0.301	15.85	93.68	0.133
23	0.256	15.80	93.66	0.665

Conclusion

The Discrete Wavelet Transform (DWT) and Run-Length Encoding (RLE) based PCG signal compression and encryption allow to store and transfer large amount of data securely and without loosing any data containing pathological Information. Our results show that the proposed PCG signal compression algorithm can achieve higher compression ratio with very less signal distortion compared to the conventional compression algorithms. Another advantage of this method is that all the information of the signal is hidden because of the encryption. The qualitative design and the analysis of this compression technique could also be used on other remote patient monitoring data management.

Future Work

- To denoise the noisy PCG signal.
- To extract all the important pathological information from the PCG signal.
- To classify the PCG signal.

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