Sinusoidal modelling for efficient source coding of phonocardiogram signals in cardiac monitoring devices

Samer Alabed[1], Mohammad Al-Rabayah[2], Bahaa Al-Sheikh[3], Lama Bou Farah[4]
[1]Department of Biomedical Engineering, School of Applied Medical Sciences, German Jordanian University, Amman, Jordan
[2]College of Engineering and Technology, American University of the Middle East, Egaila, Kuwait
[3]Department of Biomedical Systems and Informatics Engineering, Hijjawi Faculty for Engineering Technology, Yarmouk University, Irbid, Jordan
[4]Department of Biomedical Technologies, Faculty of Public Health, Lebanese German University, Sahel Aalma, Lebanon

Article Info

Article history:

Received Dec 30, 2024
Revised Aug 11, 2025
Accepted Sep 1, 2025

Keywords:

Cardiovascular disease
Electrocardiogram medical devices
Good health
Internet of things
Phonocardiogram
Sinusoidal source coding
Sustainable healthcare system

ABSTRACT

This study focuses on developing an efficient and cost-effective approach for compressing phonocardiogram (PCG) signals without compromising their quality to be used in in real-time cardiac monitoring devices. The method utilizes two data compression techniques, capturing heart sounds and transforming them into the frequency domain to extract essential features such as frequency, phase, and amplitude peaks. The compressed signals are subsequently reconstructed to faithfully replicate the original heart sounds. The findings contribute to advancements in biomedical signal processing and compression methodologies, with potential applications in telemedicine, internet of things (IoT), and remote sustainable healthcare systems. Compressed PCG signals enable real-time remote consultations and continuous cardiac health monitoring, particularly in underserved regions with limited medical resources. This research holds significant potential for improving access to cardiovascular healthcare and promoting overall health and well-being.

Corresponding Author:

Samer Alabed
Department of Biomedical Engineering, School of Applied Medical Sciences
German Jordanian University
Amman, 11180 Jordan
Email: samer.alabed@gju.edu.jo

1. INTRODUCTION

In biomedical signal processing, especially in the processing of phonocardiogram (PCG) signals, considerable advancements have taken place to treat physiological data more efficiently in transmission. The PCG acts as a crucial diagnostic instrument in cardiovascular diseases, mainly by detecting and recording heart sounds, for instance, complex movements of the cardiac structures and blood flow phenomena [1]-[3]. Traditionally, the process of auscultation consisted of infinitely listening to heart sounds with a rudimentary stethoscope [4], [5]. Some heart sounds or murmurs may remain undetectable, and no recordings are made for further analysis. The closure of heart valves generates at least two different heart sounds. First, the S1 sound is generated when the atrioventricular valves close at the beginning of systole, while the S2 sound is produced by the closure of the pulmonary and aortic valves at the end of systole.

Effective data transmission and storage are becoming more and more important as telemedicine, internet of things (IoT), and remote patient monitoring are used more frequently. Multi-antenna systems and cooperative communication techniques are used by next-generation wireless communication systems to boost signal transmission efficiency [6]-[9]. However, data rates usually must be lowered due to bandwidth limitations. Next-generation source coding techniques address this limitation by compressing data while preserving important information. Effective data encoding is made possible by methods like entropy coding and predictive coding, which guarantee the best possible bandwidth utilization without sacrificing signal quality. These systems effectively overcome bandwidth constraints by fusing next-generation source coding techniques [10]-[17] with multi-antenna technology and cooperative communication strategies [18]-[20], guaranteeing secure signal transmission. This method works best in applications like IoT and mobile networks. The use of these cutting-edge technologies promises optimal spectrum utilization and smooth connectivity for a wide range of wireless communication applications.

PCG signals present difficulties because they are data-intensive by nature, despite being information-rich by nature. This makes the need for reliable and affordable compression methods designed especially for PCG signals urgent. These signals actually record the acoustic sounds generated by the beating heart, while electrocardiogram (ECG) signals represent the electrical pulse of the heart [21]-[25]. Unique to these signals are their characteristics; understanding them would shed light on the diagnostic data contained therein. In previous research works, some processing difficulty specific to the PCG signals were pointed out, including accurate peak detection, amplitude variations, and interference from external noise. A compression method has been developed as a result of these considerations in an attempt to mitigate these issues. Although many compression techniques have been used for biomedical data, including ECG signals, specific techniques for PCG signals remain scarce. This work considers this gap by using sinusoidal coding, an approach known for maintaining main features during compression.

The need of preserving vital diagnostic characteristics while signal compression is underway has been emphasized by research [26], [27]. Although PCG signals are widely used for medical monitoring and diagnosis [28], [29] such as in ECG stress test machines, effective compression methods are required to maximize storage and transmission bandwidth due to their high data volumes. Lossless compression is a popular technique for PCG signal compression that lowers signal size without sacrificing information [10]-[13], [17], [21], [22], [30]. By breaking down signals into their frequency components, the wavelet transform, a well-known method for lossless compression, allows for effective compression of each band. Other methods, like Huffman coding and run-length encoding, have also been effectively used for PCG signal lossless compression. Another strategy is lossy compression, which sacrifices some information in order to achieve higher compression ratios (CR) [10]-[16]. One popular lossy compression technique is predictive coding, where the sample is predicted from previous ones, and the prediction error is encoded. Significant compression is accomplished with little information loss by quantizing this error. Machine learning methods have recently become effective tools for compressing PCG signals. High CR have been made possible while maintaining essential information by using deep learning algorithms, such as autoencoders, to learn compact representations of PCG signals. These techniques efficiently compress PCG signals while capturing intricate patterns.

Overall, techniques for compressing PCG signals encompass a variety of techniques from advanced machine-learning approaches to simple signal-processing methods [10]-[16]. Each technique has compromises about information loss, computational complexity, and compress ratio. Application-specific requirements for CR and willingness for information degradation has implications for the selection process for compression technique. With advancing research there will likewise new, even more effective methods which should evolve the field of PCG signal compression.

2. RESEARCH METHOD

A sinusoidal model, as described in [10], [11], offers an efficient voice-coding methodology that relies on the amplitudes, frequencies, and phases of sine waves in a PCG signal to enable both analysis and synthesis. High-quality signal reconstruction at low data rates has been successfully accomplished with this technique [10]-[13], [17], [21], [22]. It represents the k-th segment, i.e., k-th frame, of the input signal as a sum of a specific number of sinusoidal parameters, each uniquely characterized by its amplitude (A_k), frequency (Ω_k), and phase (ϕ_k):

$$sig(n) = \sum_{k=1}^{S} A_k.\sin(\Omega_k n + \phi_k) \tag{1}$$

where A_k, Ω_k, ϕ_k, and S correspond to the amplitude, frequency, phase of the k-th sinusoidal wave, and the total number of potential peaks, respectively. Sinusoidal encoders are flexible for a range of signal types because they are highly effective in handling both voiced and unvoiced segments. During the analysis stage, the parameters that correspond to the sinusoids are extracted after the input signal has first been split up into smaller frames. These extracted parameters are then used to reconstruct the original frames at the receiver side during the synthesis stage in order to effectively convert PCG signals into the frequency domain and capture the unique features of heart sounds, the signal transformation process utilizes the Sinusoidal Coding method. To improve precision in representing frequencies, the transformation algorithm employs a windowing technique such as the Hamming window.

To extract the intrinsic attributes of the PCG signals, working with the frequency domain is necessary. During the optimal feature extraction process, the essential diagnostic information required for accurate signal reconstruction is preserved. This ensures that the PCG signal is accurately reconstructed from the feature-extracted signals with the original heart sound intact. An important consideration for the PCG signal compression system is the overarching expectation of the system, the CR versus the signal fidelity. In the pursuit of a satisfactory balance between compression and preserved diagnostic data, the algorithm is modified. In the efforts to enhance the system responsiveness and seamless incorporation into healthcare frameworks, real-time implementation demands dominate the need for heavy computational efficiency. The algorithm is designed with the existing medical devices and healthcare system in mind to ensure seamless interoperability by embedding standard formats for data, storage, and transmission. For added system reliability, consistent performance across diverse signal conditions is rigorously tested.

The signal transformation approach uses ssinusoidal coding at the output of the signal transformation approach to convert the PCG signals to the time domain from the frequency domain. The MATLAB code outlines a simple method which begins with a time base of the PCG signal windowed by the Hamming window for spectral analysis. The spectral analysis used fast Fourier transform (FFT) to obtain the spectrum representation. This representation isolates the sinusoidal components needed to obtain information about the frequency, phase, and amplitude. The feature extraction method revealed useful information in the frequency domain while extracting useful features including frequency, phase, and amplitude. Reconstruction of the important features converted back to time-base so that phase information was retained to enhance the correctness of the signal. We have identified performance measures that will assist the decision-making of the design parameters of the PCG signal compression system. The measures will help evaluate the system's usefulness and ensure useful diagnostic information is retained during compression:

a. CR: the ratio between the original and transmitted bit rate which needs to be optimized to find a balance between decreasing the overall bit rate and keeping significant information.
b. Fidelity: the quality of the reconstructed PCG signal as compared to the original one. The purpose of the fidelity criteria is to maintain the compressed PCG signal's clinical dependability.
c. Real-time processing: any clinical data with time-dependent characteristics must be made available with the real-time processing specifications in the design. The system is provided with strict time limits to allow it to perfectly integrate into healthcare workflows. Consequently, the above standards would ensure that the suggested PCG compression system qualifies on its performance, reliability, and clinical usefulness standards. Thus, the following criteria were then developed:

– Signal transformation criteria
  a) Hamming window technique:
  – Chosen for its ability to suppress the side-lobes while maintaining the resolution.
  b) FFT size:
  – Selected to optimize frequency and time resolution.
  – Chosen according to the engineering standards and best practices in signal processing.
– Feature extraction criteria

The feature extraction stage plays a pivotal role in preserving diagnostic information from the PCG signal. The design criteria for this stage include:

  a) Peak-picking threshold:
  – Used to remove unnecessary data while keeping diagnostically useful characteristics.
  – Adaptable to varying signal conditions to provide robustness and reliability.
  b) Number of peaks:
  – Determined based on PCG signal diagnostic importance and complexity.
  – Capable of providing sufficient information to allow robust signal reconstruction.
– Signal reconstruction criteria

In order to give proper reconstruction of the PCG signal, the reconstruction algorithm is designed to meet some engineering requirements:

  a) Phase management:
  – Particular attention is paid to preserve phase information while reconstructing.
  – This must be done so that data is not lost and an original replica of the reconstructed signal is like the original one.
  b) Overlap and interpolation:
  – Evaluation of overlap and interpolation requirements during reconstruction.

– These values are traded-off to achieve both computational effectiveness and reconstruction accuracy within accepted engineering standards.

If we stick to these criteria, the signal transformation, feature extraction, and reconstruction methods ensure the compression system is of high fidelity, computationally efficient, and reliable, making them well-suited for clinical and real-time applications.

2.1. Encoder stage

The encoder converts the PCG segments into parameters that are quantized into binary strings and sent over a communication channel. The long-term goal of the proposed method is to drastically decrease the bit rate of PCG signal while maintaining signal integrity and perceived quality.

– Sampling and frame segmentation

The PCG signal is sampled at 8 kHz and divided into frames. Each frame is classified into one of two groups dependent on its energy level-i.e., high-energy frames and low-energy frames, as follows:

a. Voiced frames: these are frames with higher energy levels and, hence, are generally associated with carrying augmented diagnostic information.
b. Unvoiced frames: these frames have lower energy levels and need fewer peaks to represent their features.

– Subdivision and energy-based classification

In addition to that, each voiced frame is divided into N-subframes, which are also classified according to their energy levels:

a. High-energy subframes: allocated more peaks to capture the details.
b. Low-energy subframes: assigned fewer peaks to optimize the bit rate while maintaining essential information.

The hierarchical classification approach qualifies successful extraction of required parameters for low bit rate representation while ensuring that quality is not lost in reconstructing the PCG frames. The two major areas into which this encoding algorithm is divided are further elaborated in the sub-sections that follow. The classification approach has ensured an efficient as well as a fidelity-based encoding process, thereby satisfying the compression system objectives.

2.1.1. Sinusoidal peaks selection strategy

To ensure the wide-sense stationarity of the PCG signal, in the proposed method of encoding, the signal is divided into primary frames with a duration lying anywhere between 20 and 40 ms. These frames, after being windowed, are converted into the frequency domain by means of FFT so that sinusoidal peaks might be found, which are necessary for the accurate signal reconstruction on the decoders' side. Since an inherent conflict between window size and parameter resolution exists in the selection of peaks, the chief challenge in this process lies in estimating the significant peaks and their parameters and at the same time in deciding the best duration for the analysis window. On one hand, window length must be chosen as a tradeoff between competing objectives: detection of rapid variations requires short windows, whereas accurate frequency resolution and the separation of closely spaced spectral elements require longer ones. To meet this tradeoff, the analysis is performed using the Hanning window since the better side lobe suppression leads to better results in accurate peak detection.

Short-time Fourier transform (STFT) local maxima in magnitudes are used to identify the sinusoidal components in the PCG signal. A spike or a local maximum in the STFT magnitude corresponds to a sinusoidal wave. While the method is effective and is characterized by a fixed bit rate, reducing this bit rate means choosing a small number of sinusoids for encoding. To improve the performance of this step, peaks are selected with the help of a threshold, i.e., local maxima peaks surpassing that threshold are identified as sinusoidal peaks. Taking into consideration the spectral slope change, peaks are selected, especially those corresponding to high-to-low transitions. Afterward, a parabola is fitted through each peak and the vertex value of this parabola is used to compute the peak frequency. The whole process yields roughly 80 peaks. The identified peaks are reduced further, through some suitable means of reduction that may lose little in perceived information. After this reduction:

– Frequency values of the peaks, together with the important phases corresponding to them, are extracted.
– Quantization is performed on these parameters to prepare for transmission.

Final transmission: after quantization, the parameters are transmitted to the receiver so that the PCG signal can be efficiently encoded with the maintenance of diagnostic quality. Thus, the approach balances bit rate reduction and fidelity to conform to the computational and diagnostic criteria.

2.1.2. Optimization of data rate

The proposed method is to encode the significant peaks since only such a procedure would enhance the efficiency of the construction of block codes while maintaining the excellent signal properties. This is achieved in a multi-level procedure which decomposes the PCG signal into main frames and then sub-frames. The PCG signal is first segmented into main frames and labeled as voiced and unvoiced using a preconfigured energy threshold. Voiced frames, which have energy levels above an energy threshold, are split into N sub frames. More peaks are assigned to the higher-energy sub-frames and less to the lower-energy sub-frames. On the other hand, unvoiced frames, which have energy levels less than the threshold, are also split into sub-frames, but without further energy classification. All the sub-frames in the unvoiced frames are allotted the same number of peaks, which is the same as the distribution for the lowest-energy sub-frame in the voiced frames. This systematic classification and segmentation ensure that only the most significant peaks are coded, thus reducing the bit rate without compromising the fidelity of the reconstructed PCG signals.

Reduction of the number of parameters is crucial for minimizing compression and reconstruction errors. The parameter reduction works to decrease the parameters per key frame to 15-30. This is achieved by:

a. Segmented classification: ranking the most important peaks according to energy levels.
b. Quantization: in this procedure, further lowering parameter counts is done.

After classification and segmentation, three encoding stages are used to maximize parameter reduction:

a. Peak reduction: to reduce the number of necessary parameters, the most significant peaks are encoded where redundant or less important peaks are filtered out.
b. Phase reduction: keeps enough information to guarantee reconstruction fidelity while decreasing the accuracy of phase values linked to sinusoidal peaks.
c. Threshold reduction: optimizes the bit rate while preserving vital diagnostic information by introducing adaptive thresholding to remove small peaks that fall below a predetermined significance level. The suggested method successfully strikes a balance between low bit rates and high-quality signals by utilizing these three encoding levels.

– Number of peaks minimization:

The job of this phase is to discover and select N most significant sinusoidal components of every voiced frame, the value of N being predetermined in terms of target data rate. The encoding scheme of this phase involves the following steps:

a. Frequency domain transformation: every sub-frame is converted into the frequency domain using methods like the FFT in order to facilitate analysis and selection of significant sinusoidal components.
b. Peak identification: assign the most dominant tops in the frequency domain at each sub-frame as the most dominant sinusoidal components.
c. Peak selection for closely situated peaks: when peaks are tightly distributed in the frequency spectrum, select the largest peak among the group to represent the group. Redundancy is eliminated with the prime spectral information being preserved. This method ensures that the selected peaks provide a good-quality approximation of the signal and, in effect, ready it for the subsequent steps of the encoding process. By focusing on the strongest peaks and eliminating weaker peaks, the method achieves the optimal balance between data compression and signal quality, and hence forms a good foundation for further processing.

– Phase minimization:

This stage is intended to minimize the phase parameters by classifying each sub-frame as voiced or unvoiced. Voiced/unvoiced classification depends on the following voiced frame features:

a. Greater energy: voiced frames has energy values greater than a predefined threshold.
b. Zero crossings: voiced frames typically possess fewer zero crossings compared to unvoiced frames.
c. Pitch value: voiced frames possess a specific pitch value that could be utilized for separation from unvoiced frames.

Among these criteria, the first—greater energy—is the most significant for reducing overall complexity. As a result, it is implemented using a binary decision-making process. The encoding process for phase parameters is as follows:

a. Voiced frame processing: if a frame is classified as voiced (i.e., it has substantial energy content), the encoder directly extracts its phase parameters.
b. Unvoiced frame processing: for unvoiced frames, phase parameters are estimated using phase extraction equations from established methods, such as those presented by McAulay and Quatieri [10], [21], [22], or Ahmadi and Spanias [11]. By minimizing the number of phase parameters in unvoiced frames and taking advantage of human auditory insensitivity to phase distortion, the technique significantly reduces computational and data transmission demands. This approach ensures that the perceived quality of the reconstructed PCG signal remains largely unaffected while optimizing resource efficiency.

– Threshold optimization

This stage is considered the most effective of the minimization techniques described, as it focuses on significantly reducing the number of sinusoidal peaks while maintaining the perceived integrity of the signal. By applying a low threshold value, peaks with amplitudes below this threshold are systematically removed, resulting in the following benefits:

a. Peak elimination below threshold:
- Eliminates insignificant peaks to reduce the corresponding frequencies, amplitudes, and phases.
- Decreases the number of amplitudes required for encoding.

b. Noise filtration:
- Filters out noise-related peaks with low amplitudes, improving the overall quality of the recovered frames.

c. Optimized data rate:
- Reduces the overall bit rate needed for transmission. While this method improves signal quality, increasing the threshold beyond a certain point may result in corrupted frames by inadvertently filtering out critical informative peaks. Therefore, finding the optimal threshold value is important and requires an in-depth statistical study to optimize data reduction and signal quality.

After applying all reduction stages:

a. Each main frame will contain S amplitudes, S frequency values, and 0.5S phases.

b. For each main frame:
- Amplitude and frequency values: 6 bits are allocated for each.
- Phase values: 4 bits are allocated for each.

The required data rate for each frame is calculated as (2):

$$F = S \times (6+6) + (0.5S \times 4) = 12S + 2S = 14S\ bits/frame \quad (2)$$

Thus, the data rate per frame depends directly on the number of selected peaks S, ensuring efficient encoding while maintaining the quality of the reconstructed PCG signal. The total data rate (R) can be calculated as (3):

$$R = F \times N = 14S\ (bits/frame) \times N\ (frames/s) = 14NS\ bps \quad (3)$$

Extra bits can be reserved for functions such as control, error detection, and error correction to enhance system reliability and performance.

2.1.3. Advantages of the proposed coding technique

As outlined in the preceding section, the proposed coding approach demonstrates several notable features and benefits:

- Effective and efficient stages: incorporates highly effective and efficient encoding and decoding processes, optimizing performance.
- High-quality signal reconstruction: produces a high-quality reconstructed PCG signal at the receiver's side, ensuring fidelity to the original signal.
- Reduced data rate: achieves a significantly reduced data rate in the range of 4-8 kbps, enhancing transmission efficiency.
- Noise robustness: improves the reconstructed signal's quality even in the presence of noise, maintaining diagnostic accuracy.
- Pitch independence: operates independently of the fundamental pitch, making it versatile and applicable to a variety of PCG signals.
- High noise immunity: possesses good noise immunity, which ensures operation under harsh settings.
- Power and bit rate optimization: leads to a power and bit-rate-minimized transmission; hence it is suited for applications with limited resources, such as telemedicine or IoT medical devices and systems.
- Error handling capability: allows for the implementation of error detection and correction techniques to achieve more reliable data transmission. This coding technique reflects a well-rounded approach to PCG signal compression with respect to quality, efficiency, and robustness and thereby becomes a convenient coding alternative for actual healthcare applications.

3. RESULTS AND DISCUSSION

The first step to compress the PCG signal was to translate the proposed technique into working MATLAB code, allowing for a thorough test of the performance and determining where improvements could be made. The implementation started with the process of signal transformation where a Hamming window was used while the FFT transformed PCG signals into the frequency domain to establish a foundation for feature extraction. Second, peak-picking based feature extraction software was employed to identify significant frequency peaks from the transformed signals with promising outcomes for the overall extraction of the fundamental features applied in signal reconstruction. Peak-picking based feature extraction software carried out this significant task. Finally, a reconstruction algorithm converted the extracted features to the time domain. Initial testing revealed no clear differences between the original and the reconstructed PCG signals, which verified high fidelity. Examination continued to show that the incoming signals were similar in form and all applicable properties to the original signals, Figures 1 to 3. The primary functionality of the compression unit was extensively tested by a first MATLAB model. The signal transformation, feature extraction, and reconstruction algorithms worked perfectly to preserve the integrity of the PCG signal and were very promising in terms of real-world applications. Future advances and enhancements will focus on raising computational capability and robustness and optimizing the system in real-word PCG and ECG medical devices and stress test machines.

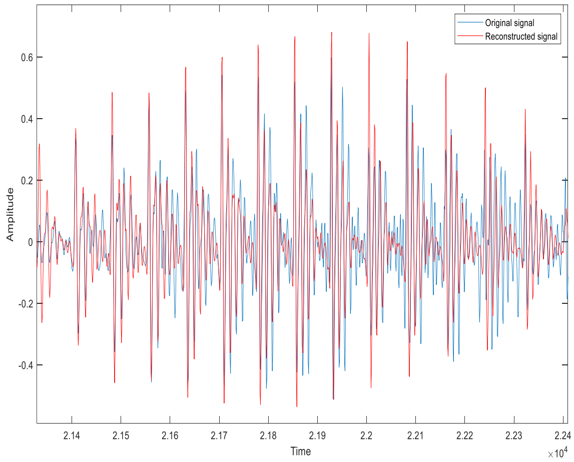

Figure 1. Difference between the original signal and the reconstructed signal

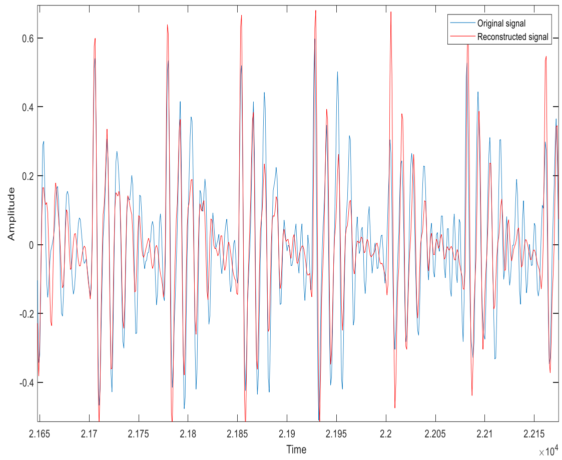

Figure 2. Representation of several frames in the PCG signal

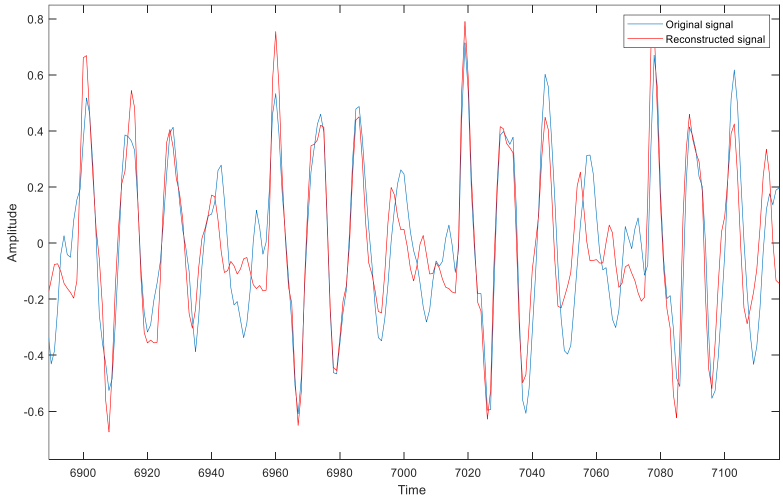

Figure 3. Shape of a single frame accurately and more clearly

The implementation phase is a comprehensive evaluation of the PCG signal compression algorithm to ensure it performs satisfactorily with real-time data taken from a well know datasets. The algorithm was tested for reliability and applicability in scenarios by applying it to several PCG datasets of actual cardiac recordings taken from a well-known databases. Typical and key performance parameters were systematically and thoroughly analyzed and included the CR, which measures the capacity for data reduction; the mean squared error (MSE), which gives accuracy of reconstruction; and the signal-to-noise ratio (SNR), which ensured preservation of some quality of the signal during reconstruction. The algorithm was measured under various conditions, namely, different noise levels and amplitude changes with different cardiac pathologies, to check consistency and robustness. Although it is able to maintain high fidelity in reconstruction and perform compression very efficiently, it has a few downsides with regards to noise sensitivity and time delays during computation. For that matter, some modifications are suggested that go towards fixing these problems like adaptive peak-picking thresholds for handling signal variation, better phase handling through advanced approaches such as interpolation, and optimized real-time processing. These improvements aim to make the system more robust, adaptable, and reliable for real-world healthcare applications such as real-word PCG and ECG medical devices and stress test machines.

4. CONCLUSION

The primary objective of this work was to develop a technique for compressing PCG signals that significantly reduces data size and is also capable of restoring high-quality signals for making accurate cardiac diagnoses. Sinusoidal coding was utilized to achieve this, providing an economical approach that is specially devised for telemedicine and low-resource healthcare systems. Iterative design and rigorous testing resulted in the effective application of the method of compression, obtaining the best balance between effectiveness of compression and diagnostic accuracy. The ultimate design had a better Sinusoidal coding algorithm that had the capability to compress PCG signals in an effective manner while retaining critical diagnostic information, offering a special means for characterizing cardiac activity in a summarized and dependable way.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to the German Jordanian University, the American University of the Middle East, and Aeon Medical Supplies Company for their generous support of this work.

FUNDING INFORMATION

This work was funded by Seed Grant number SAMS 03/2023 from the German Jordanian University, under decision number 2023/15/344. Additional support was provided by a grant from Aeon Medical Supplies Company, by the American University of the Middle East, and by the Scientific Research and Innovation Support Fund (SRISF), Jordan, under project number SE-MPH/4/2024. The authors express their gratitude for these generous supports.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Samer Alabed	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mohammad Al-Rabayah				✓		✓			✓	✓		✓	✓	✓
Bahaa Al-Sheikh				✓		✓	✓			✓	✓	✓		
Lama Bou Farah				✓		✓	✓			✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] T. Chakrabarti, S. Saha, S. Roy, and I. Chel, "Phonocardiogram signal analysis - Practices, trends and challenges: A critical review," in *2015 International Conference and Workshop on Computing and Communication (IEMCON)*, Vancouver, BC, Canada, Oct. 2015, pp. 1–4, doi: 10.1109/IEMCON.2015.7344426.

[2] M. S. Obaidat, "Phonocardiogram signal analysis: Techniques and performance comparison," *Journal of Medical Engineering & Technology*, vol. 17, no. 6, pp. 221–227, Jan. 1993, doi: 10.3109/03091909309006329.

[3] L. G. Durand and P. Pibarot, "Digital signal processing of the phonocardiogram: Review of the most recent advancements," *Critical Reviews in Biomedical Engineering*, vol. 23, no. 3–4, pp. 163–219, 1995, doi: 10.1615/CritRevBiomedEng.v23.i3-4.10.

[4] B. Ergen, Y. Tatar, and H. O. Gulcur, "Time-frequency analysis of phonocardiogram signals using wavelet transform: A comparative study," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 15, no. 4, pp. 371–381, Apr. 2012, doi: 10.1080/10255842.2010.538386.

[5] S. Y. Lee, P. W. Huang, J. R. Chiou, C. Tsou, Y. Y. Liao, and J. Y. Chen, "Electrocardiogram and Phonocardiogram Monitoring System for Cardiac Auscultation," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 6, pp. 1471–1482, 2019, doi: 10.1109/TBCAS.2019.2947694.

[6] T. Abood, I. Hburi, and H. F. Khazaal, "Massive MIMO: An Overview, Recent Challenges, and Future Research Directions," in *ICASEA 2021 - 3rd 2021 International Conference on Advance of Sustainable Engineering and its Application*, Wasit, Iraq, Oct. 2021, pp. 43–48, doi: 10.1109/ICASEA53739.2021.9733081.

[7] S. A. Khwandah, J. P. Cosmas, P. I. Lazaridis, Z. D. Zaharis, and I. P. Chochliouros, "Massive MIMO Systems for 5G Communications," *Wireless Personal Comms*, vol. 120, no. 3, pp. 2101–2115, Oct. 2021, doi:10.1007/s11277-021-08550-9.

[8] S. Alabed, "Computationally efficient multi-antenna techniques for multi-user two-waywireless relay networks," *International Journal of Electrical and Computer Engineering*, vol. 8, no. 3, pp. 1684–1691, Jun. 2018, doi: 10.11591/ijece.v8i3.pp1684-1691.

[9] Y. Huo *et al.*, "Technology Trends for Massive MIMO towards 6G," *Sensors*, vol. 23, no. 13, pp. 1–22, Jun. 2023, doi: 10.3390/s23136062.

[10] R. J. McAulay and T. F. Quatieri, "Speech analysis/synthesis based on a sinusoidal representation," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 34, no. 4, pp. 744–754, Aug. 1986, doi: 10.1109/TASSP.1986.1164910.

[11] S. Ahmadi and A. S. Spanias, "New techniques for sinusoidal coding of speech at 2400 bps," in *Conference Record of the Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, CA, USA, 1997, pp. 770–774, doi: 10.1109/acssc.1996.601158.

12] J. Jensen, S. H. Jensen, and E. Hansen, "Harmonic exponential modeling of transitional speech segments," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, Istanbul, Turkey, 2000, pp. 1439–1442, doi: 10.1109/ICASSP.2000.861884.

[13] R. Vafin, S. V. Andersen, and W. B. Kleijn, "Exploiting time and frequency masking in consistent sinusoidal analysis-synthesis," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, Istanbul, Turkey, 2000, pp. 901–904, doi: 10.1109/ICASSP.2000.859106.

[14] S. K. Ghosh, A. Ray, R. K. Tripathy, and R. N. Ponnalagu, "A Transform Domain Approach for the Compression of Fetal Phonocardiogram Signal," *IEEE Sensors Letters*, vol. 5, no. 5, pp. 1–4, May 2021, doi: 10.1109/LSENS.2021.3074985.

[15] H. Naseri and M. R. Homaeinezhad, "Detection and boundary identification of phonocardiogram sounds using an expert frequency-energy based metric," *Annals of Biomedical Engineering*, vol. 41, no. 2, pp. 279–292, Feb. 2013, doi:10.1007/s10439-012-0645-x.

[16] P. T. Krishnan, P. Balasubramanian, and S. Umapathy, "Automated heart sound classification system from unsegmented phonocardiogram (PCG) using deep neural network," *Physical and Engineering Sciences in Medicine*, vol. 43, no. 2, pp. 505–515, 2020, doi: 10.1007/s13246-020-00851-w.

[17] I. Mansour and S. Alabed, "Using sinusoidal model to implement sinusoidal speech coder with speech enhancer," in *The 6 th International Electrical and Electronics Engineering Conference (JIEEEC)*, 2006, pp. 1–8.

[18] C. Qi, Y. Huang, and S. Jin, "Overview of massive MIMO system," *Shuju Caiji Yu Chuli/Journal of Data Acquisition and Processing*, vol. 30, no. 3, pp. 544–551, 2015, doi: 10.16337/j.1004-9037.2015.03.009.

[19] S. Alabed, M. Al-Rabayah, and W. H. F. Aly, "A Beamforming Technique Using Rotman Lens Antenna for Wireless Relay Networks," *Computers, Materials and Continua*, vol. 73, no. 3, pp. 5641–5653, 2022, doi: 10.32604/cmc.2022.030371.

[20] S. Alabed, "Noncoherent distributed beamforming in decentralized two-way relay networks," *Canadian Journal of Electrical and Computer Engineering*, vol. 43, no. 4, pp. 305–309, 2020, doi: 10.1109/CJECE.2020.2991404.

[21] R. J. McAulay and T. F. Quatieri, "Magnitude-Only Reconstruction Using a Sinusoidal Speech Model," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, San Diego, CA, USA, 1984, pp. 441–444, doi: 10.1109/ICASSP.1984.1172492.

[22] R. J. McAulay and T. F. Quatieri, "Phase Modelling and Its Application To Sinusoidal Transform Coding," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, Tokyo, Japan, 1986, pp. 1713–1715, doi: 10.1109/icassp.1986.1169250.

[23] C. Xu *et al.*, "Hearing Heartbeat from Voice: Towards Next Generation Voice-User Interfaces with Cardiac Sensing Functions," in *SenSys 2022 - Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems*, 2022, pp. 149–163, doi: 10.1145/3560905.3568508.

[24] T. H. Chowdhury, K. N. Poudel, and Y. Hu, "Time-Frequency Analysis, Denoising, Compression, Segmentation, and Classification of PCG Signals," *IEEE Access*, vol. 8, pp. 160882–160890, 2020, doi: 10.1109/ACCESS.2020.3020806.

[25] H. Namazi and O. Krejcar, "Analysis of Pregnancy Development by Complexity and Information-Based Analysis of Fetal Phonocardiogram (PCG) Signals," *Fluctuation and Noise Letters*, vol. 20, no. 4, p. 2150028, Aug. 2021, doi: 10.1142/S0219477521500280.

[26] A. K. Abbas and R. Bassam, *Phonocardiography Signal Processing*, in Synthesis Lectures on Biomedical Engineering, Cham: Springer International Publishing, 2009, doi: 10.2200/S00187ED1V01Y200904BME031.

[27] A. Thalmayer, S. Zeising, G. Fischer, and J. Kirchner, "A robust and real-time capable envelope-based algorithm for heart sound classification: Validation under different physiological conditions," *Sensors*, vol. 20, no. 4, pp. 972–992, Feb. 2020, doi: 10.3390/s20040972.

[28] M. M. Bassiouni, I. Hegazy, N. Rizk, E. S. A. El-Dahshan, and A. M. Salem, "Combination of ECG and PPG Signals for Smart HealthCare Systems: Techniques, Applications, and Challenges," in *Proceedings - 2021 IEEE 10th International Conference on*

Intelligent Computing and Information Systems, ICICIS 2021, Cairo, Egypt, Dec. 2021, pp. 448–455, doi: 10.1109/ICICIS52592.2021.9694241.

[29] B. Zhu, Z. Zhou, S. Yu, X. Liang, Y. Xie, and Q. Sun, "Review of Phonocardiogram Signal Analysis: Insights from the PhysioNet/CinC Challenge 2016 Database," *Electronics*, vol. 13, no. 16, pp. 3222–3249, Aug. 2024, doi: 10.3390/electronics13163222.

[30] S. Alabed, A. Alsaraira, N. Mostafa, M. Al-Rabayah, Y. Kotb, and O. A. Saraereh, "Implementing and developing secure low-cost long-range system using speech signal processing," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 3, pp. 1408–1419, Sep. 2023, doi: 10.11591/ijeecs.v31.i3.pp1408-1419.

BIOGRAPHIES OF AUTHORS

Samer Alabed is a Professor of biomedical and electrical engineering and Director of accreditation and quality assurance center at German Jordanian University (GJU). He served as a Director of e-learning and academic performance improvement center, head of biomedical engineering department and exchange coordinator at GJU and was an associate professor at American University of the Middle East, Kuwait, from 2015 to 2022. He also studied and worked in Darmstadt University of Technology, Darmstadt, Germany, from 2008 to 2015. He can be contacted at email: Samer.Alabed@gju.edu.jo.

Mohammad Al-Rabayah earned his Ph.D. in Electrical Engineering from University of New South Wales. He is serving as an Associate Professor at American University of the Middle East (AUM), where he teaches a variety of courses, advises students, and contributes to departmental excellence. He was an Assistant Professor at Prince Sultan University. During his tenure, he taught courses in the Communication and Networks Department and played a key role in supporting the university's efforts to achieve ABET accreditation. He can be contacted at email: Mohammad.Alrabayah@aum.edu.kw.

Bahaa Al-Sheikh received Ph.D. in Biomedical Engineering from University of Denver, Colorado, USA. From 2009 to 2015, he worked for Yarmouk University as an assistant professor and served as the department chairman from 2010 to 2012. He worked as an Assistant and Associate Professor at the American University of the Middle East in Kuwait from 2015 to 2019. He works now as an Associate Professor at Yarmouk University. He can be contacted at email: alsheikh@yu.edu.jo.

Lama Bou Farah is currently an Associate professor, Head of the Biomedical technologies Department, Acting Head of the Medical Imaging, Department and Academic Quality Coordinator at the Lebanese German University. She received her Ph.D. degree in Biomedical Engineering and Advanced Medicine from Macquarie University, Australia. She has worked as an associate professor, assistant professor, researcher, and lecturer in several international universities and supervised tens of master students and several Ph.D. students. She received several awards and grants. She can be contacted at email: l.boufarah@lgu.edu.lb.