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TUNABLE FOETAL ECG COMPRESSION USING DINGO OPTIMIZATION ALGORITHM AND WAVELET TRANSFORM

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Abstract— A novel method of efficient communication between a medical professional and a patient is made possible by wireless communications. The present heart state of the patient can be efficiently sent to the physician's phone using these techniques. Although there are a number of key technologies that make wireless healthcare facilities appealing, efficient compression is absolutely necessary. It is vital to develop higher compression without incurring the cost of losing data. The scientific community's activities in healthcare telemedicine are motivated by the requirement for biomedical signal compression. This paper presents Tunable Foetal Electrocardiography (ECG) signal compression using the Dingo Optimization Algorithm and Wavelet Transform that shows better average Compression Ratio (CR) at much lower User specified Percentage root mean square difference (UPRD). The overall result show that for total 26 records, average CR increases by 1.03 % and 2.39 %, when UPRD increases from 0.5 to 1 and from 0.5 to 2 respectively.

Keywords— Foetal ECG Signal, Noninvasive Detection, Compression, Dingo Optimization Algorithm, Wavelet Transform cdf9/7

Introduction

The electrical activity of the developing Foetus's heart can be seen on the Foetal Electrocardiography (ECG), which can be obtained over the Foetal scalp. Because medical practitioners cannot observe the Foetus as they do other patients, it requires regular monitoring and care. Even the Foetus is safe in the natural environment, but there are a number of cardiac disorders, such as intrauterine hypoxia and Foetal distress, that must be considered for the mother and baby's well-being. Doctors can tell how well a Foetus' heart is working by monitoring Foetal heartbeats. If any irregularities are discovered, therapy can begin immediately, potentially saving both the mother and the unborn child's lives. Wireless technologies enable Foetal conditions to be regularly transmitted to doctors' portable devices. A smart phone-based system for monitoring the Foetal ECG was suggested by Yuan et al. [1]. Data compression is anticipated for these devices because continuous monitoring of foetal with cardiac arrhythmia generates a large amount of data. Compression is crucial for preserving memory space and enhancing transmission efficiency as data volume rises over time. Gao presented Non-invasive Detection and Compression of Foetal ECG in 2017 [2]. Arican and Polat [3] in 2018 proposed a new technique for compressing the foetal ECG signal based on data compression with variance. In this experiment, the non-interference Foetal ECG database was used, and it was shown that the time domain characteristics of the compressed and raw CEKG signals did not significantly differ (mean change, 0.053%). As a result, compression of 20% to 40% was achieved. Abhishek and Veni [4] developed the Sparsity Improving Wavelets Design for ECG and Foetal ECG Compression in 2022.

In engineering and biomedical data analysis applications, the use of meta-heuristic optimization algorithms is steadily expanding due to their reliance on simple ideas and ease of implementation, lack of dependence on gradient information, capacity to avoid local optima, and ability to be applied to a wide range of problems spanning numerous disciplines. Meta-heuristic algorithms that draw inspiration from nature address optimization issues by reproducing natural events. Another approach for dealing with optimization issues is the Dingo Optimization Algorithm (DOA). The Australian dingo dog's social behaviour is reminiscent of the DOA. The algorithm relies on dingo hunting techniques, which attack by persecuting, grouping, and scavenging. To improve the overall effectiveness and performance of this system, the DOA developed three search strategies linked to four rules. They hunt opportunistically and will scavenge food if they come upon dead prey while scouting out new area. They frequently approach and hunt prey from behind. Their preferred method of hunting is a collective attack, in which they encircle and pursue the target until it becomes exhausted [5].

The Discrete Wavelet Transform (DWT) [6] is formed by uninterruptedly laying low-pass and high-pass filters to the discrete time-domain data. The main components of a filter bank include delay elements, decimators, expanders, and low pass and high pass filters. Forward Wavelet Transform employs filter banks known as analysis filters, whereas Inverse Wavelet Transform uses filter banks known as synthesis filters. The 9/7-tap bi-orthogonal Cohen-Daubechies-Feauveau (CDF) filter is also known as the Daubechies (db9/7) wavelet filter. There are symmetric scaling and wavelet functions. They are especially favored for picture compression applications because of these qualities [6].

Despite the fact that there haven't been many studies on the compression of Foetal ECG signals, none of them are perfect. As a result, the process of condensing the Foetal ECG signal must be improved. To improve the Foetal ECG signal compression method, an adjustable strategy based on the wavelet transform and the Dingo Optimization Algorithm [5] is proposed.

Performance Metrices

The Percentage of Root Mean Square Difference (PRD) and the Compression Ratio (CR) are two decisive parameters that are frequently employed in performance monitoring. The ratio between a signal's uncompressed original size and its reduced size is known as the compression ratio (CR). By dividing the signal's compressed and uncompressed sizes, it is determined [4].

CR = Uncompressed size/Compressed size

PRD is calculated as [1]:

$$PRD = 100 \times \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x}_i)^2}{\sum_{i=1}^{N} x_i^2}} \qquad (1)$$

where the i^{th} sample of the original and reconstructed foetal ECG signal, both of length N, are denoted by the letters x_i and $\bar{x}_i$ When comparing the findings of an ECG with a foetal ECG signal, PRD is used more commonly than any other statistic since it is the most straightforward.

A quite good reconstruction is one with a PRD under 2%, a decent reconstruction with a PRD under 9%, and a bad reconstruction with a PRD under 19% for medical examination [4].

Methodology

Any abnormal or normal Foetal heart rhythm that exceeds the reference range of 100 to 200 beats per minute is referred to as a Foetal cardiac arrhythmia (bpm). 10% of arrhythmic Foetuses are thought to be potential morbidity sources. Arrhythmias affect about 1% of all Foetuses. Most Foetal arrhythmias are harmless, but a small number can result in Foetal hydrops and even death. As a result, one Foetus out of every 100 requires constant monitoring and, if necessary, in-utero anti-arrhythmic medication [7]. Four to five abdominal channels and one maternal chest channel were recorded for each recording. The sampling rate was specified in the file header as 500 Hz or 1 kHz [9].

A brief overview of recorded cases of non-invasive foetal electrocardiography (NI-FECG) with a focus on Arrhythmias Rhythm (ARR) and Normal Rhythm (NR) is presented here. The study includes a total sample size of 26 recordings, with 12 cases falling under the Arrhythmias Rhythm category and 14 cases under Normal Rhythm.

The average duration of NI-FECG records for the Arrhythmias Rhythm group is approximately 13 minutes and 3 seconds, while for the Normal Rhythm group, it is about 10 minutes and 6 seconds. Gestational age is an essential factor in foetal development, and in this study, the Arrhythmias Rhythm group had an average gestational age of 32 weeks, with a standard deviation of ±6.8 weeks. In contrast, the Normal Rhythm group had an average gestational age of 23 weeks, with a standard deviation of ±4.8 weeks.

Furthermore, the number of events detected in the NI-FECG recordings is another significant parameter. The Arrhythmias Rhythm group recorded an average of approximately 46.8 events with a standard deviation of ±34.5, while the Normal Rhythm group detected only around 2 events on average, with a standard deviation of ±2.6.

Additionally, the visibility of P-waves, which is crucial in detecting certain heart conditions, was measured. The Arrhythmias Rhythm group exhibited a P-wave visibility percentage of 83%, while the Normal Rhythm group had a slightly lower percentage of 57% [8].

The compression and performance analysis of Foetal ECG signals involve several key steps [15]. Firstly, the user specifies the desired Percentage of Root Mean Square Difference (PRD) and a threshold value (TH) [16] is chosen using the dingo optimization algorithm, with a convergence precision (ϵ) set at 1% [10]. The Foetal ECG signal is then transformed using the Wavelet Transform cdf 9/7. Next, a copy of the transformed coefficients (TC) is taken, and the thresholding process is applied to these coefficients using the F16(x) function, optimized with the dingo algorithm.

For Optimization function is

$$F_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$$

For Dingo Optimization Algorithm Variable =2, Range [-5,5] and fmin=-1.0316 is used.

The inverse Wavelet Transform is then performed to reconstruct the compressed Foetal ECG signal. The PRD is computed by comparing the original Foetal ECG signal with the reconstructed signal [11]. If the calculated PRD is less than the user-specified PRD (UPRD), the algorithm checks whether the relative difference between PRD and UPRD (PRD − UPRD / UPRD) is greater than the convergence precision (ϵ) [12]. If it is, the thresholding process is adjusted, and the steps are repeated to improve compression. Once the PRD requirement is met, a binary lookup table is constructed to represent zero and non-zero coefficients obtained after thresholding, and this table is encoded using Huffman coding [13]. The non-zero coefficients are then quantized using the Max-Lloyd algorithm, followed by Arithmetic coding [14] for efficient encoding. The end result is a final compressed representation of the Foetal ECG signal, achieving reduced data size and minimal loss of information.

Results and Discussions

From Table 1, 26 records with Wavelet Transform cdf 9/7, average CR increases by 1.03% and 2.39%, when UPRD increases from 0.5 to 1 and from 0.5 to 2 respectively. There was an increase in the CR with an augmented of UPRD value for each wavelet transform cdf 9/7. To achieve the best reconstructed signal quality, UPRD is kept within the range of 0.5 to 2, as CR increases with increasing UPRD, but after a certain value of UPRD, the reconstructed signal is unrecognizable [4]. Within the data, for arrhythmia rhythm 12 samples at UPRD 0.5, CR varies from minimum value 4.21 to maximum 12.8 and for UPRD 2, this range is 4.44 to 12.93. For normal rhythm 14 samples CR varies for 7.73 to 12.33 and 7.93 to 12.67 at UPRD 0.5 to 2 respectively. It could be because normal rhythm samples are more repeatable than abnormal rhythm samples, resulting in a higher CR. When compared to Abhishek, S., and Veni, S. [4], and Polania et al. [17], the current work achieved approximately same average CR at a much lower UPRD from Table 2.

Table 1. Performance of DOA and Wavelet Transform cdf 9/7 on different Foetal ECG signals.

Duration= 1 min; quantization bits= 12;									
Foetal ECG Signals	UPRD1=0.5			UPRD1=1			UPRD1=2		
	BPRD[2]	QPRD[3]	CR[4]	BPRD[2]	QPRD[3]	CR[4]	BPRD[2]	QPRD[3]	CR[4]
ARR_01m	0.50	0.51	9.24	1.00	1.01	9.34	2.00	2.00	9.47
ARR_02m	0.50	0.50	11.03	1.00	1.01	11.14	2.00	2.00	11.32
ARR_03m	0.50	0.51	6.67	1.00	1.00	6.79	2.02	2.02	6.90
ARR_04m	0.50	0.50	9.42	1.00	1.00	9.62	2.00	2.00	9.72
ARR_05m	0.50	0.51	11.91	1.00	1.01	12.01	1.99	1.99	12.13
ARR_06m	0.50	0.50	4.21	1.01	1.01	4.28	2.00	2.00	4.44

ARR_07m	0.50	0.51	5.64	1.00	1.01	5.71	2.00	2.00	5.89
ARR_08m	0.50	0.53	11.31	1.00	1.02	11.32	2.00	1.98	11.36
ARR_09m	0.50	0.52	5.51	0.99	1.00	5.54	1.99	1.99	5.63
ARR_10m	0.50	0.52	12.80	1.00	1.02	12.85	2.01	2.00	12.93
ARR_11m	0.50	0.53	11.05	1.00	1.01	11.05	2.01	2.02	11.08
ARR_12m	0.50	0.50	9.55	1.01	1.01	9.69	2.00	2.00	9.83
NR_01m	0.50	0.52	10.96	1.01	1.02	11.05	2.00	2.01	11.26
NR_02m	0.50	0.51	10.11	1.00	1.00	10.22	1.99	1.99	10.34
NR_03m	0.50	0.52	11.24	1.01	1.01	11.31	2.00	2.00	11.49
NR_04m	0.50	0.53	10.82	1.00	1.00	10.92	2.00	2.00	11.10
NR_05m	0.50	0.50	9.18	1.00	1.00	9.30	2.00	2.00	9.35
NR_06m	0.50	0.51	11.01	1.00	1.00	11.15	1.98	1.98	11.28
NR_07m	0.50	0.51	7.73	0.99	1.00	7.77	1.99	1.99	7.93
NR_08m	0.50	0.50	9.37	1.00	1.00	9.51	2.02	2.02	9.64
NR_09m	0.50	0.51	8.78	0.99	1.00	8.89	2.00	2.00	9.03
NR_10m	0.50	0.52	11.00	1.01	1.00	11.14	2.01	2.01	11.30
NR_11m	0.50	0.51	10.48	1.00	1.00	10.57	2.00	2.00	10.71
NR_12m	0.50	0.65	12.33	1.00	1.03	12.55	2.00	2.01	12.67
NR_13m	0.50	0.50	11.03	1.00	1.01	11.14	1.99	1.99	11.32
NR_14m	0.50	0.53	7.74	1.00	1.00	7.77	2.01	2.01	7.93
Mean	0.50	0.52	9.62	1.00	1.01	9.72	2.00	2.00	9.85

1UPRD=User defined PRD 2BPRD= Before quantization PRD

3QPRD= After quantization PRD 4CR= Compression ratio

Table 2: Comparison of proposed method with the Literature [4].

	CR (average)	PRD (average)
Abhishek, S., and Veni, S. [4]	10	3.2
Proposed method	9.85	2

Conclusions

To save bandwidth, energy, storage requirements, time, and many more, and to make the most of telemedicine techniques, it is necessary to compress the signal before transmission and reconstruct the replica of original signal at the receiver side, with the condition that the reconstructed signal be as close to the original signal as possible. In this study, efforts were made to achieve higher average CR at lower UPRD for Foetal ECG signals. According to the findings, the Dingo Optimization Algorithm and Wavelet Transform increase average CR by 1.03% and 2.39%, when UPRD is increased from 0.5 to 1 and from 0.5 to 2 respectively. A comparison of Foetal ECG signals using various optimization techniques and wavelet filters could be done in the future.

References

[1] Yuan, Li, Yanchao Yuan, Zhuhuang Zhou, Yanping Bai, and Shuicai Wu. "A fetal ECG monitoring system based on the android smartphone." Sensors 19, no. 3 (2019): 446.102773.

[2] Gao, Xin. "Non-invasive detection and compression of fetal electrocardiogram." Cardiac Electrograms-From Skin to Endocardium, InTechOpen (2017): 53-74.

[3] Arıcan, Murat, and Kemal Polat. "A novel fetal ECG signal compression method: Variance and neighboring based data compression [Yeni bir Cenin EKG sinyali sikistirma yöntemi: Varyans ve Komsuluk Tabanli Veri Sikistirma]." In 26th IEEE Signal Processing and Communications Applications Conference, SIU 2018. Institute of Electrical and Electronics Engineers Inc., 2018.

[4] Abhishek, S., and S. Veni. "Sparsity enhancing wavelets design for ECG and fetal ECG compression." Biomedical Signal Processing and Control 71 (2022): 103082.

[5] Peraza-Vázquez, Hernán, Adrián F. Peña-Delgado, Gustavo Echavarría-Castillo, Ana Beatriz Morales-Cepeda, Jonás Velasco-Álvarez, and Fernando Ruiz-Perez. "A bio-inspired method for engineering design optimization inspired by dingoes hunting strategies." MathematicalProblems in Engineering 2021 (2021): 1-19.

[6] Pascal Getreuer, waveletcdf97.m from Matlab file Exchange website.

[7] Behar, Joachim A., Laurent Bonnemains, Vyacheslav Shulgin, Julien Oster, Oleksii Ostras, and Igor Lakhno. "Noninvasive fetal electrocardiography for the detection of fetal arrhythmias." Prenatal diagnosis 39, no. 3 (2019): 178-187.

[8] https://archive.physionet.org/cgi-bin/atm/ATM

[9] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., and Stanley,H. E. PhysioBank, PhysioToolkit. "Physionet: components of a new research resource forcomplex physiologic signals." Circulation 101, no. 23 (2000): e215-e220.

[10] Aggarwal, Vibha, Sandeep Gupta, Manjeet Singh Patterh, and Lakhwinder Kaur. "Analysis of compressed foetal phono-cardio-graphy (PCG) signals with discrete cosine transform and discrete wavelet transform." IETE Journal of Research 68, no. 4 (2022): 2736-2742.

[11] Aggarwal, Vibha, Manjeet Singh Patterh, and Virinder Kumar Singla. "Comparative studies of discrete cosine transform and lifting wavelet transform techniques for compression of blood pressure signal in salt sensitive Dahl rat." International Journal of Computational Systems Engineering 4, no. 2-3 (2018): 165-170.

[12] Aggarwal, Vibha, Sandeep Gupta, Manjeet Singh Patterh, and Lakhwinder Kaur. "Quality Controlled EMG Signal Compression using Linear and Non Linear Transforms." International Journal of Innovative Technology and Exploring Engineering (IJITEE) 8, no. 12 (2019):5885- 5889.

[13] Aggarwal, Vibha, and Manjeet Singh Patterh. "ECG signal compression using morphological haar wavelet transform." Int J Eng Sci 17 (2016): 263-265.

[14] Aggarwal, Vibha, and Manjeet Singh Patterh. “Analysis and development of ECG compression techniques.” LAP LAMBERT Academic Publishing, 2013.

[15] Aggarwal, Vibha, Sandeep Gupta, Shipra Bansal, and Priyanka. “Seismocardiogram Signal Compression using DCT and DWT.” Journal of Critical Reviews 7, no. 09 (2020): 3406 – 3409.

[16] Aggarwal, Vibha, and Manjeet Singh Patterh. “ECG Signal Compression using Normalization and Thresholding.” International Journal of BioSciences and Technology 5, no. 8, (2012): 40– 44.

[17] Polania, Luisa F., Rafael E. Carrillo, Manuel Blanco-Velasco, and Kenneth E. Barner. "Compressed sensing based method for ECG compression." In 2011 IEEE international conference on acoustics, speech and signal processing (ICASSP), pp. 761-764. IEEE, 2011.