Comparison of Data Compression Methods for Implanted Real-time Peripheral Nervous System

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***Abstract*— Research in the development of neuroprostheses aims to restore the loss bodily and motor functionalities. In order to have effective solutions, the physiological signals used to control neuroprostheses must be first measured and then properly reconstructed. Miniaturized electronic enables the realization of implantable devices suitable for the treatment of pathologies that cannot be cured with conventional medicine. However, given the limited data processing and transmission capabilities of microcontroller-based implantable devices, data compression algorithms must be developed with minimal distortion upon reconstructions. Although several compression techniques are available in the literature, a suitable strategy for compression of electroneurographic (ENG) signals has not yet been defined so far. The main goal of this work is to propose a pipeline to perform the compression of biomedical data. The approach is validated on available recordings of ENG signals. As main contribution, we applied different compression algorithms to the recorded ENG signals that were obtained in response to mechanical stimulation of a rat paw. A combination of lossy and lossless techniques was studied by measuring the performance in terms of time required for data compression, compression ratio, and distortion. To evaluate the use in real-time applications, the robustness of the techniques has been tested considering a temporal constraint of 300 ms.**

Keywords—ENG signals, sciatic nerve, data compression, real time application, wireless data transmission.

I. Introduction

Thousands of new cases of peripheral nerve injury occur every year in Europe, Japan, and United States. A nerve injury can cause varying degrees of deficit, ranging from a muscle weakness to a complete loss of sensory and motor function in areas innervated by the affected nerve. Therefore, the resulting medical condition can dramatically impair individuals' quality of life [1]. Traditional medicine approaches are presently unable to solve this clinical issue. However, thanks to the progress of miniaturized technologies, a new type of medical market that involves the use of implanted devices is emerging. Since these devices typically include microcontrollers, which have limited capabilities in terms of signal processing, storage, and transmission rate, suitable data compression algorithms must be developed in order to reduce the computational demand and to minimize the distortion introduced on the measured signal.

Data transfer from implanted devices is often realized with a Bluetooth 5 Low Energy (BLE5) interface, which can achieve a maximum transmission rate of 2 Mbps. To enable real-time applications on patients, the compression techniques in implanted devices must be able to handle the largest amount of data within the constraint defined by the maximum transmission rate [2]. Clearly, if from one side data compression allows to satisfy transmission within the limits of the used wireless technology, from the other it might introduce severe signal distortion.

Contributions and Applicability

The main objective of this work is the study of compression techniques that can be applied to electroneurographic (ENG) signals for reducing the data rate. As is well known, there are several options to achieve its decrease. These go from a simple reduction of the sampling frequency to the use of complex encoding methods. In this work we investigate compression approaches with contribution to the:

1. definition of a pipeline to achieve a minimum distortion in the compression of ENG data;
2. evaluation of the performance of different compression methods in terms of efficiency, required time, and reconstruction error in a real-time scenario;
3. verification that the total processing time, which is given by the sum of the delay introduced by the compression technique and that needed for the transmission, is lower than the human response time of 300 ms, thus allowing to correctly restore the motor function [2].

II. State-of-the-Art of Compression Algorithms for Biomedical Signals

Data compression methods are a well consolidated topic in signal processing [4]. They are typically implemented as the sequential combination of a lossy technique like, for example, Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT), and lossless compression algorithms. Some of the most used in the latter category are Run-Length Encoding (RLE) [5], GNU Zip encoding (GZIP) [6], Zip Compression Library encoding (ZLIB) [6], High Compression variant of Lempel-Ziv 4 encoding (LZ4HC) [7], and Delta Encoding (DE) [8]. The combination allows to obtain a good trade-off between compression and distortion, which means the best possible data rate reduction by guaranteeing the minimum reconstruction error in the shortest possible time. The lossless algorithms give small compression ratio (CR), while lossy algorithms guarantee high CR at the cost of information loss. It has been observed that hybrid methods give the best performance in terms of quality of the reconstructed signal [9]-[11].

With reference to hybrid compression techniques applied to biomedical signals, only few compression techniques have been proposed in the literature. The study in [9] proposed an electroencephalogram (EEG) compression algorithm based on wavelets and wavelet packets where the coefficients are quantized and encoded using an RLE. In [10] a new approach was proposed to compress electrocardiogram (ECG) data, which involves the combined use of DWT and Huffman coding. Finally, [11] considered the use of JPEG2000, which consists in the application of DWT followed by arithmetic coding.

III. Flowchart of the Proposed ENG Data Compression

A. Data Set

The data set selected to evaluate the performance of the studied compression algorithms is provided by the University of Newcastle [3]. It contains raw ENG signals obtained from the measures of mechanical stimulations of the paw of three healthy Sprague Dawley rats. The dataset contains signals from 16 channels detected by a multi-contact cuff electrode positioned on the sciatic nerve. The signals are characterized by an amplitude up to 50 µV and a main bandwidth between 800 Hz and 3 kHz.

With the aim of standardizing and homogenizing the results obtained from the rats, it has been analyzed the proprioceptive signals: dorsiflexion and plantarflexion. The ENG signals were generated by alternating phases of exercise with phases of rest each 3 sec [3, 12, 13].

The performance of the compression algorithms was tested via MATLAB R2021a on a PC equipped with Intel(R) Celeron(R) N4000 CPU @ 1.10GHz, operating system 64-bit, and x64-based processor. We have verified that similar performances can be obtained with other processors.

B. Data Compression

In this paper, for the compression of ENG data we evaluate hybrid approaches based on the use of transforms combined with lossless compression algorithms. The block diagram of the implemented algorithms is shown in Fig. 1.

With reference to the figure, the first operation is a non-linear thresholding to limit the range of amplitudes of the rough signal in the interval ±50 µV. This is required because not all the ENG data are usable. In fact, due to disturbances in the measurement equipment, some parts of the recorded signals are very noisy, and therefore their amplitude must be limited to achieve a better performance. Then, the data processing flow envisages the application, first, of a transformation and then of a lossless compression algorithm preceded by a quantization process to digitize the data. Finally, the representative binary data is obtained, which can be wirelessly transmitted.

To enhance the robustness and achieve a high CR an additional thresholding (set to 0.5) is introduced in case the DCT is performed. This allows us for further control over the level of lossy compression in the signal. Samples below the specified threshold are considered irrelevant and are assigned a value of zero. By selecting the appropriate threshold level, it is possible to attain better CR while minimizing any adverse impact on the fidelity of the resulting signal.

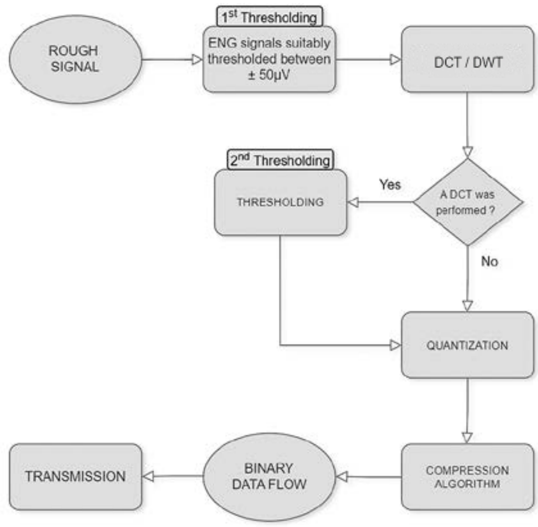


Figure 1: Block diagram of the hybrid compression schemes with thresholding.

IV. Quality Metrics

The main performance metrics [4] used in the analysis of the different compression methods are the following:

- *Compression Ratio* (CR), which indicates how much the data has been reduced. Let

$$v = [v_1, v_2, \dots, v_n] \tag{1}$$

be the vector of n ENG signal samples and

$$v' = [v'_1, v'_2, \dots, v'_m] \tag{2}$$

be that of m compressed samples. By introducing the length reduction factor as

$$\mathcal{E} = \frac{m}{n} \tag{3}$$

and the ratio between the size of the data types in bits (integer, double, float, …) as

$$\lambda = \frac{size(data\ type\ v')\ \ [bits]}{size(data\ type\ v)\ \ [bits]}, \tag{4}$$

the CR turns out to be by the product

$$CR = \mathcal{E} \cdot \lambda. \tag{5}$$

- *Percentage Root mean square Difference* (PRD), which gives the distortion in the reconstructed signal. It is defined as

$$PRD = \frac{\|x - \hat{x}\|}{\|x\|} \cdot 100\ (\%), \tag{6}$$

where x and $\hat{x}$ are the original and the reconstructed signal, respectively, and $\|\cdot\|$ is the Euclidean norm.

- *Compression Time* (CT) and *Transmission Time* (TT), which are dependent on the used processor and the used wireless technology. For these measures, two cases were considered:
  - o*ffline approach,* which involves the compression of the entire matrix containing the data collected from all the electrodes;
  - *online approach,* which consists in compressing windows of different temporal durations (50, 250, and 500 ms).

Note that, the lower is the value of each of the above metrics and the better is the performance of the specific algorithm. For the offline case, the performances were evaluated for all the techniques listed in Sec. II. For the online approach, the performance was tested only for the best and the worst three techniques of the offline case. Thanks to our analysis it is possible to concretely evaluate how these techniques behave in view of a future real application on a human patient.

For the offline approach, only the CT and the decompression time (DT) were calculated (excluding the TT) to highlight how long it takes the algorithm to reconstruct the data starting from the transmitted ones.

Regarding the evaluation of the time in the online approach, three metrics were calculated: the CT, which is the execution time of the compression algorithms, the TT, which is the time spent in the transmission of the compressed data, and the total time CT+TT, which is given by the sum of the previous two. The transmission protocol is BLE 5 implemented on Nordic® nRF52805 RF chip, having a theoretical bit-rate of 1.4 Mbit/s and a real one of 1 Mbit/s. The compression performance was evaluated by computing the Mbits of the compressed data. This quantity turns out to be the product of the sampling frequency f_s (in this work set to 30 kHz), the number of selected channels N_{ch} (contacts, set equal to 16 for the cuff electrode size), the size of the data packet in bits (set equal to 8 if data set is an integer or to 16 in others case of float), the window length $size_{win}$ of the time interval considered for the compression (in sec), and the CR^*, which indicates how much the data (samples) have been reduced. The computation gives

$$\text{Mbits} = f_s(\text{MHz}) \cdot N_{ch} \cdot size(data\ type) \cdot size_{win} \cdot CR \quad (7)$$

Since the compression technique must be implemented in real-time applications, due to the latency introduced by the transmission and the subsequent operations (preprocessing, classification, and other operations such as neuromodulation), the total duration of the cumulative operation made for the data compression should be less than 300 ms (human sensory response [2]). Therefore, it is necessary to define an indicative threshold that establishes whether the implemented algorithm is acceptable or not. In this regard, the residual value (RT, Redundancy Time) can be defined, which indicates how much time is still available to carry out further operations to stay under the human response. It is equal to the tolerable limit of the human sensory response minus the total time taken by each delay operation for the compression and transmission (so CT and TT) in one specific window (50, 250, 500 ms):

$$RT = 300\ \text{ms} - window - (CT + TT). \quad (8)$$

Note that, the introduction of the RT allows us to consider suitable or not a proposed algorithm for real-time applications only if its value is positive.

V. NUMERICAL RESULTS

The CR and PRD are calculated for both offline and online approaches. In the first case, the CT and the CT+DT are also measured, to compare the different algorithms. For the second case, in addition to the CT, the total time taken to CT and TT the data for the different time windows is also calculated. The DE has been studied separately because is not used in combination with transforms.

A. Offline Approach

As a result of several data compressions, the offline metrics were evaluated for the three datasets discussed in Sec. III. Results are reported in Tables 1, 2, and 3 as averages over each if the three animals for dorsiflexion and plantarflexion. The best and the worst three algorithms were obtained by analyzing in detail the behavior of CR, PRD, and CT. A discussion about the criteria used for their evaluation will be done in Sec. VI.

B. Online Approach

For the online case, we wanted to highlight how CR, PRD, and CT varied in each time window considering only the ENG segments from the start to the end of stimulations, i.e., the useful part of the signal. The remaining part of the signal and its noisy parts were discarded.

TABLE 1: QUALITY METRICS OF DWT + LOSSLESS METHODS FOR OFFLINE APPLICATION

DWT + Lossless Methods	CR (1)	PRD (%)	CT (s)	CT&DT (s)
GZIP	0.33	26.5	21	22.8
ZLIB	0.32	26.5	21	22.2
LZ4HC	0.43	26.5	163.8	164.4
RLE	0.71	26.5	21	171

TABLE 2: QUALITY METRICS OF DCT + LOSSLESS METHODS FOR OFFLINE APPLICATION

DCT + Lossless Methods	CR (1)	PRD (%)	CT (s)	CT&DT (s)
GZIP	0.91	3.85	62.4	74.4
ZLIB	0.82	3.85	55.8	58.8
LZ4HC	1.04	3.85	390.6	396.6
RLE	1.54	3.85	44.4	343.6

TABLE 3: QUALITY METRICS OF DE FOR OFFLINE APPLICATION

	CR (1)	PRD (%)	CT (s)	CT&DT (s)
DE	1	10.30	16.8	47.4

Once the window was fixed, the metrics were calculated for all the traces, reporting a slight variability in the results. Since the signal has not undergone preprocessing to clean up any noise, the median value for each window has been reported. Fig. 2 shows how the different metrics vary with the window length.

VI. ANALSYS AND DISCUSSION OF NUMERICAL RESULTS

A. Analysis of the Offline Approach

Selected techniques are very similar to each other, and the PRD tends to increase when the CR value decrease. In addition, DCT turns out to be better than DWT in terms of PRD (less than 4 %) for any technique. Therefore, it is preferred not to decrease the information content inside the signal for a future classification application. On the contrary, DWT turns out to be better than DCT with respect to the CR, but with a greater computational complexity.

In summary, Table 1 highlights that DWT in combination with ZLIB satisfactorily provides good performance and an average PRD of 26 %. In Table 2 it can be observed that the combination of DCT with GZIP and ZLIB provide the best performance in terms of CR, PRD, and CT. These are considered valid approaches since their performance is superior to all other proposed algorithms. LZ4HC and RLE, despite their intrinsic simplicity, are quite effective even if the obtained CR is not meaningful, i.e., its value is too high. The two methods also give a PRD very low, i.e. within 4 %. In Table 3, DE has a unitary CR, which means no compression.

In conclusion, the three algorithms that provide the best compromise between compression and distortion are:

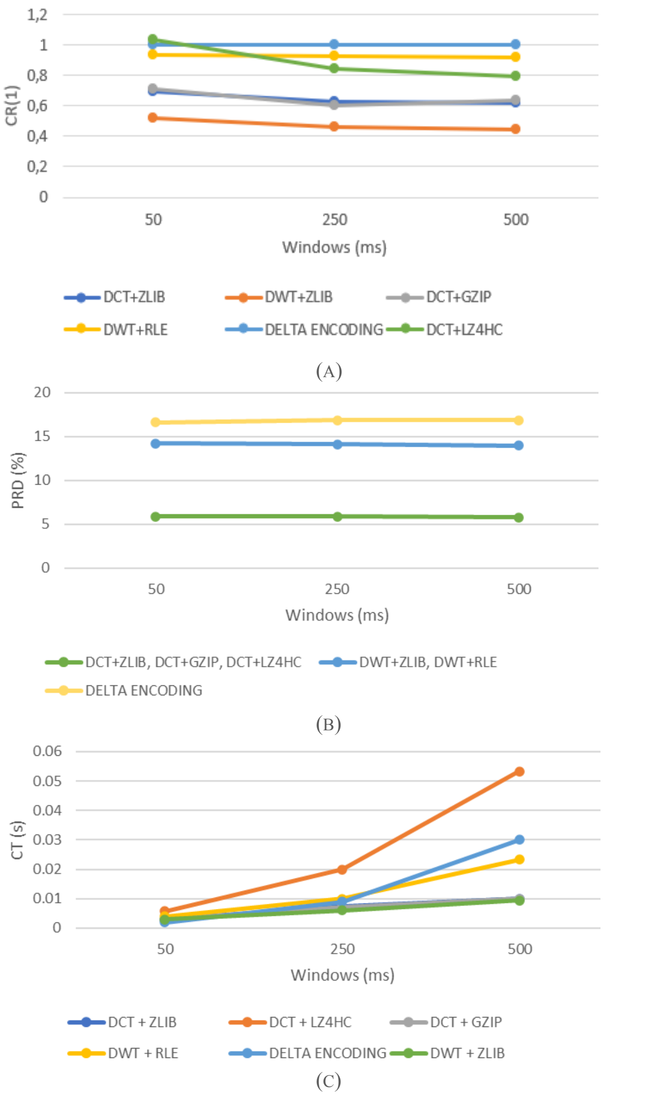


FIGURE 2: MEAN QUALITY METRICS OF (A) CR (B) PRD, AND (C) CT FOR ONLINE APPLICATION.

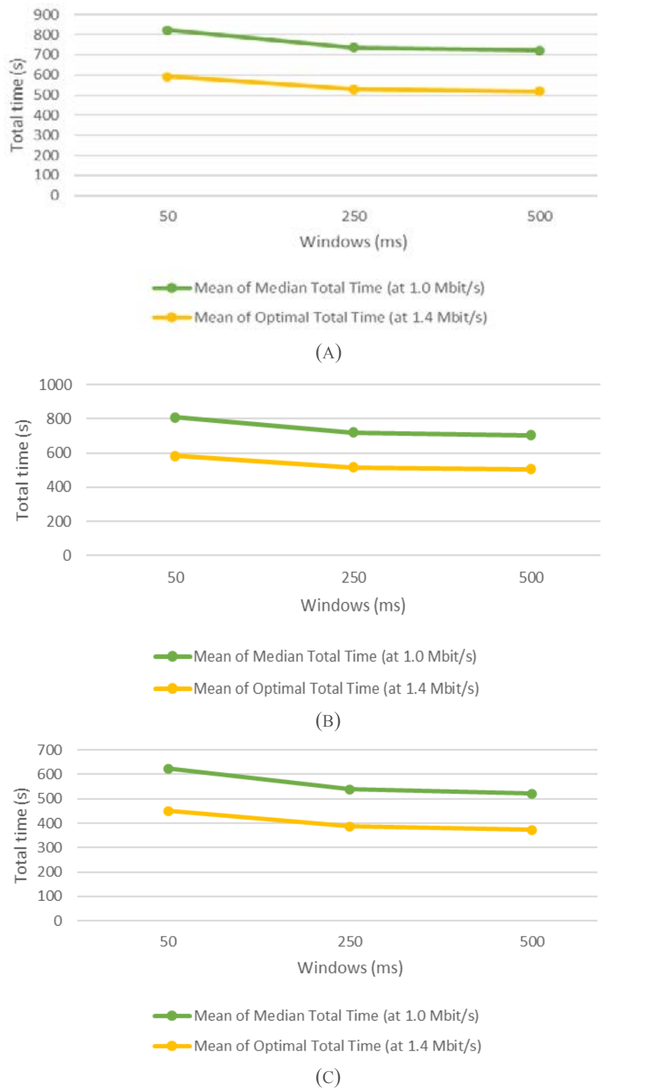


FIGURE 3: MEAN QUALITY METRICS OF TOTAL TIME INCLUDING CT+TT FOR (A) DCT + GZIP, (B) DCT + ZLIB AND (C) DWT + ZLIB FOR ONLINE APPLICATION.

- DCT + GZIP;
- DCT + ZLIB;
- DWT + ZLIB.

On the other hand, the three compression algorithms that provide the worst compromise turn out to be:

- DE;
- DCT + LZ4HC;
- DWT + RLE.

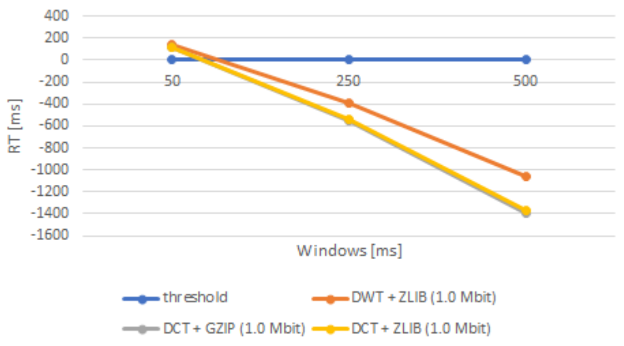
B. Analysis of the Online Approach

Next, we focused on the comparative analysis of the three best algorithms and the three worst algorithms considering different time windows.

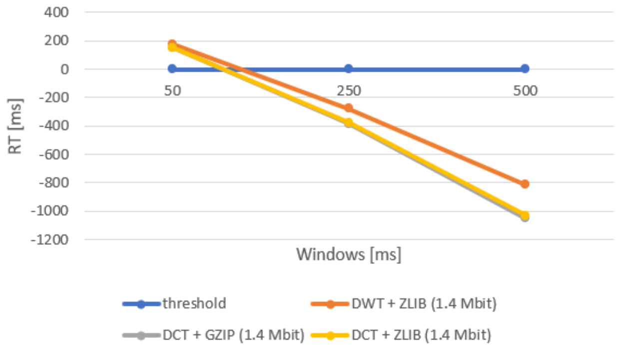
As it can be seen from Fig. 2a, the CR varies as a function of the time window. In particular, for all the algorithms the CR tends to increase as the compression window size decreases. DWT + ZLIB achieves the best CR (on average, around 0.45) followed by DCT in combination with GZIP and ZLIB (CR equal to, on average, 0.6). Anyway, the three worst methods provide a CR lower than unity, except for DCT combined with LZ4HC that, considering increasingly smaller windows, gets worse, with an increase in the CR (time windows of 50 ms are compressed giving a value of 1.03). A comparison of the results reported in Fig. 2b with those in Tables 1, 2, and 3, reveals that for the online approach the PRD values are lower and approximatively constant for the DE (25%), the DWT (15%), and the DCT (7%). These results are independent on the type of considered lossless algorithm and depends only on the lossy technique. In general, we observed that techniques with higher PRD exhibits lower CR.

Considering CT, Fig. 2c shows how for increasingly larger windows, the different techniques take longer time to compress the data, especially if the segment contains high numbers of samples (e.g., 500 ms). Unlike the other methods, DCT + LZ4HC is the slowest.

In addition, Fig. 3 shows the total cumulative time given by the sum of all CT obtained using a fixed window and the associated transmission TT. From the figure it can be seen that signal compression allows to reduce the final data size saving a lot of time for the transmission. But it is fair to point out that the total time is dominated by the TT, which in turn depends on the CR obtained. Since the TT in this case is cumulative, its value depends on the total number of windows to be compressed given their length, on the CR obtained by



(A)



(B)

FIGURE 4: RT FOR THE 3 BEST TECHNIQUE FOR BLE REAL DATA TRANSMISSION 1.0 MBIT (A) AND OPTIMAL ONE 1.4 MBIT (B) FOR ONLINE APPLICATION.

compression, and on the transmission bit-rate of the BLE5. The figures show two transmission cases, an optimal one, with 1.4 Mbit/s, and a real one, with 1 Mbit/s (due to interference during transmission).

Concerning with RT, Fig. 4 shows the remaining time available to perform different operations (i.e., preprocessing, classification, and neuromodulation) after data compression to stay under the human sensory response [2]. The results in Fig. 4 are for a single window, not the cumulative values as for Fig. 3 where results are shown only for the three techniques that obtained the best metrics. From Fig. 4 it is evident that 50 ms windows are optimal for real-time application compared to the others. The RT results are equal for both the cases: the real case of BLE5 communication at 1.0 Mbit/s, Fig. 4a, and the optimal case at 1.4 Mbit/s, Fig. 4b. In general DWT + ZLIB was found to be the combination that guaranteed the highest RT. The greater is the external communication interference, the lower the RT value will be.

C. Complexity Analysis

A generalization of the average computational complexity regarding the compression (relative time in sec and relative power consumption in bytes, see the specifications of the device used and the version of MATLAB in Sec. III) of the three best and the three worst algorithms relative to the offline case is provided in Table 4. From the table we see that DCT combined with GZIP is the most efficient from an energy point of view and this motivates its use in real-time applications for implantable devices. The DCT combined with ZLIB is the second best, while DWT combined with ZLIB uses more energy, and therefore it is more computationally demanding although the compression efficiency is much higher.

TABLE 4: GENERALIZATION OF THE COMPUTATIONAL COMPLEXITY OF THE COMPRESSION

Techniques (Transformation + Quantization + Coding)	**Time (s)**	**Allocated Memory (MATLAB, Kb)**
DCT + GZIP	74.03	$2.40 \cdot 10^6$
DCT + ZLIB	87.32	$2.41 \cdot 10^6$
DWT + ZLIB	87.54	$9.86 \cdot 10^6$
DCT + LZ4HC	466.46	$2.47 \cdot 10^6$
DWT + RLE	828.40	$1.09 \cdot 10^7$
DE	640.50	$3.20 \cdot 10^6$

To understand better how the compression facilitates the decrease of power in wireless transmission see [14].

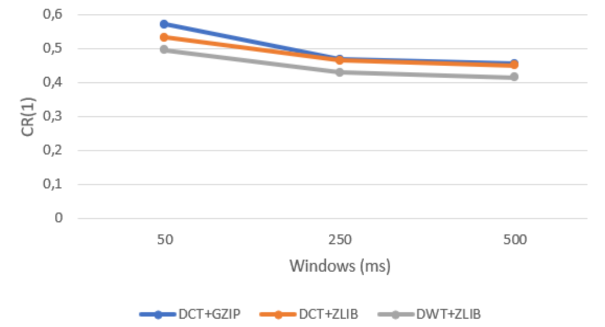
D. Downsampling of the Data Set at 10 kHz

The robustness of the compression was assessed by downsampling the raw data set at 10 kHz, to see how the various best algorithms would behave in the case of different ENG signals. As shown in Fig. 5a, the CR decreases as the time window increases, bringing the value above 0.5 for the three best techniques. In particular, DWT + ZLIB obtains a CR of up to 0.41. The values shown in Fig. 5a are obtained by comparing the downsampled ENG with the compressed downsampled one. In order to compare the CR metric with that of the original signal, the values shown in Fig. 5a must be multiplied by 0.33 (so the CR for DWT + ZLIB with the original is 0.13). For the PRD, in Fig. 5b it is shown that the values worsen, bringing its values to 14 % for DWT and to 12.5 % for DCT. The behavior remains consistent with what seen before, that is, by varying the amount of data with windowing or downsampling the proportionality between CR and PRD is constant. No significant variations are present as far as the time parameters are concerned, as shown in Fig. 2c and Fig. 5c.

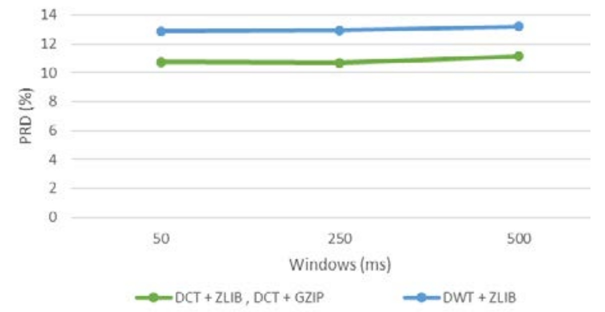
VII. CONCLUSION

In this paper we have analyzed the performance of different compression techniques for implantable devices in peripheral nervous system applications. We have proposed a pipeline for processing biomedical nerve signals based on the combination of transform and lossless compression algorithms. The goal was to perform a compression of the ENG signals in order to reduce the amount of data and the necessary time to transmit them. The compression not only decreases the power required for data transmission but also reduces the overall device power consumption. In real-time applications, the quantitative results show the superiority of ZLIB and GZIP in combination with DCT and DWT over other methods. Good CR are achievable, PRD remain within 7 % (for DCT), power consumption is decreased compared to sending the entire signal uncompressed, and the morphology of the input signal is well preserved. About the compression window size for future applications the 50 ms window should be considered for real-time applications as it leads to a good compromise between the various compression metrics. In summary, our results have revealed that DCT and DWT in combination with GZIP or ZLIB is a powerful tool for compressing ENG signals.

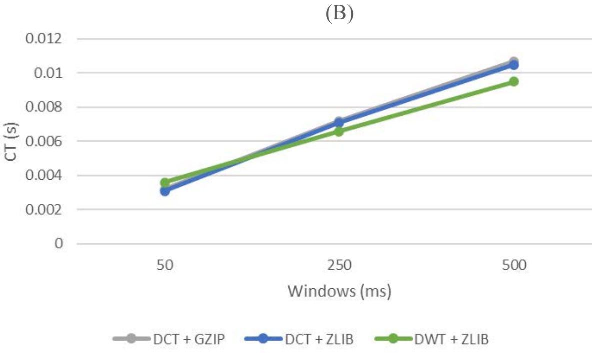
Despite their intrinsic simplicity, we have found them quite



(A)



(B)



(C)

FIGURE 5: MEAN QUALITY METRICS OF (A) CR (B) PRD, AND (C) CT FOR ONLINE APPLICATION WITH DOWN-SAMPLING.

effective and, although the compression efficiency is not too high, they represent the best option among the proposed solutions.

Although this research has focused on data compression techniques that can be implemented in a biomedical implantable device, and the same methodology can be applied to explore more innovative techniques. Consequently, in case of a large amount of data to be handled during a data transmission, hybrid data compression algorithms such as the ones reported can be used. The analysis can be extended to any type of signal presenting this type of problem for the purpose of real time-applications.

Further investigations may be conducted modetail about the window size to be used for compression and other compression algorithms not covered within this article, such as algorithms for image compression [15].

VIII. ACKNOWLEDGMENT

We would like to thank all the people members of the PNRelay group work. Sincere thanks are given to the researchers at Newcastle University for sharing their data.

REFERENCES

[1] D. Grinsell and C. P. Keating, “Peripheral nerve reconstruction after injury: a review of clinical and experimental therapies,” *BioMed Research International*, 2014.

[2] T. R. Farrell and R. F. Weir, “The optimal controller delay for myoelectric prostheses,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, Vol. 15, pp. 111-118, Jan. 2007.

[3] E. Brunton, C. Blau, C. Silveira, and K. Nazarpour, “Identification of sensory information in mixed nerves using multi-channel cuff electrodes for closed loop neural prostheses,” in *Proc. Int. IEEE/EMBS Conf. on Neural Eng. (NER)*, May 2017, pp. 391-394.

[4] U. Jayasankar, V. Thirumal, and D. Ponnurangam, “A survey on data compression techniques: From the perspective of data quality, coding schemes, data type and applications,” *J. King Saud Univ. - Comput. Inf. & Info. Sci.,* Vol. 33, No. 2, pp. 119-140, 2021.

[5] J. Capon, “A probabilistic model for run-length coding of pictures,” *IRE Trans. Inf. Theory.*, Vol. 5, No. 4, pp. 157-163, 1959

[6] “*History of Lossless Data Compression Algorithms,*” (2019, Jan. 22) Accessed on: July 30, 2023. [Online]. Available: https://ethw.org/History_of_Lossless_Data_Compression_Algorithms.

[7] Y. Collet (2011, Jan. 11), “*RealTime Data Compression - Entropy evaluation: small changes in benchmark corpus*,” Accessed on: July 30, 2023. [Online]. Available: https://fastcompression.blogspot.com/search?q=LZ4HC.

[8] S. Smith, “Data Compression - Delta Encoding,” in *The Scientist and Engineer's Guide to Digital Signal Processing*, 1997.

[9] J. Cárdenas-Barrera, J. Lorenzo-Ginori, and E. Rodríguez-Valdivia, “A wavelet-packets based algorithm for EEG signal compression,” *Med. Inform. Internet Med.*, Vol. 29, No. 1, pp. 15-27, 2004.

[10] M. S. Manikandan and S. Dandapat, “Wavelet-based electrocardiogram signal compression methods and their performances: A prospective review,” *Biomed. Signal Process. Control,* Vol. 14., pp. 73-107, 2014.

[11] K. Srinivasan, J. Dauwels, and M. Reddy, “A two-dimensional approach for lossless EEG compression,” *Biomed. Signal Process. Control,* Vol. 6, No. 4, pp. 387-394, 2011.

[12] A. Coviello, F. Porta, M. Magarini, and U. Spagnolini, “Neural network-based classification of ENG recordings in response to naturally evoked stimulation”, in *Proc. of ACM Intern. Conf. Nanoscale Comput. Commun.*, Oct. 2022, pp. 1–7.

[13] C. Silveira, E. Brunton, S. Spendiff, and K. Nazarpour, “Influence of nerve cuff channel count and implantation site on the separability of afferent ENG,” *J. Neural Eng*., Vol. 15, No. 4, pp. 046004, Aug. 2018.

[14] C. J. Deepu, C.-H. Heng, and Y. Lian, “A hybrid data compression scheme for power reduction in wireless sensors for IoT,” *IEEE Trans. Biomed. Circuits Syst.,* Vol. 11, No. 2, pp. 245-254, April 2017.

[15] A.J. Hussain, Ali Al-Fayadh, and Naeem Radi, “Image compression techniques: A survey in lossless and lossy algorithms,” *Neurocomputing*, 2018, 300, pp. 44-69.