Comparison of Imaging and Data Prediction Compression Methods for Implanted Real-Time Peripheral Nervous System

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***Abstract*— This study focuses on the problem of reducing the transmission rate of electroneurographic (ENG) signals for implantable medical devices. Such devices represent a significant innovation in the healthcare sector. We examine seven compression algorithms by implementing a variety of techniques that includes, among the others, image compression and predictors. Our results show that Fractal Compression (FC) and Vector Quantization (VQ) algorithms are the most effective, with a low value of percentage root difference (PRD), acceptable Compression Ratio (CR), and temporal redundancy. The analysis suggests that the optimal time window for compression should be between 10 ms and 50 ms. Our findings indicate that the FC and VQ algorithms could be suitable for real-time application, opening promising avenues for future research in the field of neural interfaces.**

Keywords—Wireless transmission, data compression, real-time applications, ENG signal.

I. Introduction

Medical devices have emerged as a cornerstone of contemporary healthcare, significantly enhancing societal well-being by elevating the quality of life and extending longevity. Implantable medical devices, especially neural interfaces, represent a revolutionary advance in medical technology, offering a new hope to patients with neurological disabilities that are currently untreatable by traditional medicine [1]. An example of neuropathy that is currently untreatable is peripheral lesions. When a nerve is damaged, the communication between the brain and the target organ is disrupted, causing an impairment. An implanted device can be used to treat the condition by creating a neuronal bypass [2].

In general, those devices are complex, consisting of three main operations, as shown in Fig. 1. First (blue), the signal propagating in the nerve is measured positioning the electrodes, using a stable nerve interface that allows measurement, such as the use of a cuff electrode. Next (green) the signal sampled by the implanted device using the cuff electrode must be processed, and finally (red), the extracted information will be used to electrically stimulate the distal portion to restore the connection. The implanted device usually is made by an acquisition system (analog to digital converter), filtering for preprocessing (and antialiasing), blanking circuit for neuro stimulation, a microcontroller with defined memory and computational power, a system for external communication and the power supply. It must be considered that the structure involved is highly complex and has limitations. One of the main limitations associated with implanting an electronic device is the microcontroller itself [2]. Being an implanted device, it has limited memory and computing capacity. In addition, constraints associated with the safety of the system impose a limitation to the power to be delivered to avoid any overheating. For these reasons, in order to reduce the computational load on the implanted device, it is recommended to use an external support device that, without energy, memory and calculation constraints, can perform the analysis of the acquired signal (yellow).

Another problem is the limitation on the data rate imposed by the used transmission technology. As reported in [3], the amount of data can exceed the transmission capacity of a standard antenna, such as Bluetooth Low Energy (BLE5) systems, which can reach a theoretical transmission rate of up to 2 Mbps. In addition, it is crucial to consider that this type of application must be designed to operate in real-time. Therefore, compression methods can be developed to lighten the computational load. Data compression could allow for an acceleration in information processing, provided that the total execution time remains below 300 ms, which is the threshold of human perception. Studies such as [2] have shown that it is possible to perform this type of operation while staying within the tolerance time, underscoring the importance of studies of this type. For this reason, seven compression algorithms are proposed in this work to optimize the data transmission for the ENG signal. The investigated compression algorithms are all taken from image and prediction methods.

II. Data Compression

One strategy to optimize data transmission, given the limited throughput, is data compression [4]. Within this topic, some algorithms have already been implemented specifically for ENG [3]. These algorithms represent the first compression methods documented in the literature for ENG. According to

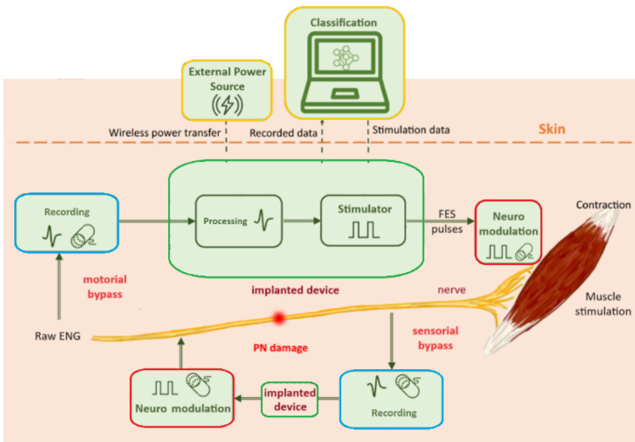

Figure 1 Diagram depicting the flow of operations necessary for the realization of a neuronal, sensory and motor bypass [2].

[3], these are typically implemented as the sequential combination of lossy and lossless techniques. In particular, those include spatial or spectral correlation and psycho-visual redundancy, involving decoding or transforming raw data into a more compressible domain (lossy), quantization for better image mapping (lossy) and entropic encoding for true image compression (lossless).

Specifically, in [3] lossy methods, such as the Discrete Cosine Transform (DCT) and the Discrete Wavelet Transform (DWT), are implemented with lossless algorithms. Among the most used lossless algorithms are Run-Length Encoding (RLE), GNU Zip (GZIP), Zip Compression Library (ZLIB), High Compression Lempel-Ziv 4 (LZ4HC) and Delta Encoding (DE). These combinations allow to obtain a good compromise between compression and distortion, reducing the data rate to the maximum with the minimum reconstruction error in the shortest possible time. The techniques that achieved the best performances were DCT + GZIP, DCT + ZLIB and DWT + ZLIB.

In general, the techniques implemented in [3] are generally used for the compression of non-biological signals. In order to evaluate different compression strategies and expand the available literature on compression techniques, seven new algorithms have been implemented and tested in this paper. The novelty of this study is to implement compression algorithms specifically adapted to ENG signals.

The compression techniques used in the study include various **image compressors** such as [5, 6, 7]: Joint Photographic Experts Group (JPEG) [8], JPEG 2000 [9, 10], fractal compression (FC) [11, 12, 13], vector quantization (VQ) [14], and Lempel-Ziv-Welch (LZW) [15, 16]. These techniques take advantage of redundancies and correlations in images to reduce the number of bits required for representation. Some common techniques include spatial or spectral correlation and psycho-visual redundancy. Taken together, these techniques for performing compression include: decoding or transforming the raw data into a domain that is easier to compress (lossy), followed by quantization for better image mapping, and entropic encoding that performs true image compression (lossless).

In addition, **predictors** such as Differential Pulse Code Modulation (DPCM) [17, 18] and Adaptive Differential Pulse Code Modulation (ADPCM) were also used [11, 19]. These techniques make it possible to estimate the values of the data based on the previous ones, reducing the size of the file by representing the error between the predicted data and the original. Effectiveness depends on the prediction model and the chosen parameters, such as the order of the predictor, which affects accuracy and computational cost. Simple models with order 1 are preferred to reduce the encoding time, but suitable for signals with low variability, as in the case of the ENG signal. Taken together, these techniques for performing compression include: implementation of the losser (lossy), quantization, and encoding algorithm (lossless).

Compared to the study performed in [3], image compressors are also employed for signals of biological origin (neuronal or muscular). Consequently, we explored the application of these compressors to the ENG signal to verify if it was possible to obtain a higher level of compression while keeping the reconstruction error low compared to other techniques. The advantage over the techniques of [3] is that these methodologies are designed to minimize information loss, being essential for biomedical images not to lose critical data for diagnostic purposes.

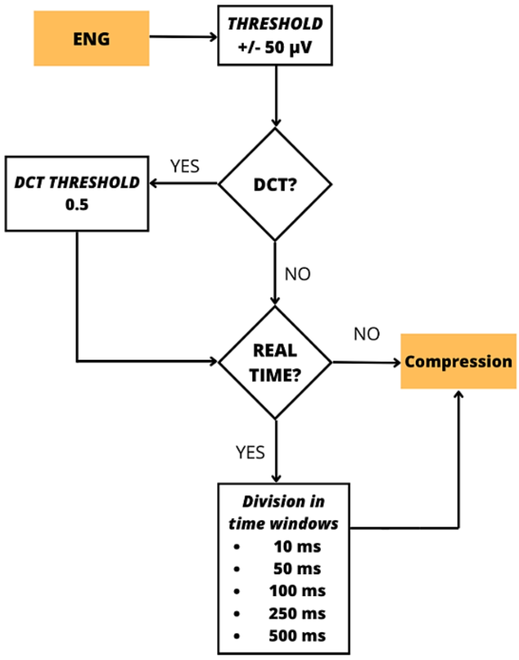

Figure 2 Preprocessing before compression.

A preliminary analysis was carried out in offline mode, identifying the JPEG 2000, FC, VQ and DPCM algorithms as the best in terms of performance. These algorithms were then tested online to determine which ones were more and less effective.

III. Compression Flowchart

The dataset used to evaluate the performance of the different algorithms are the same as that used in [3]. The dataset is described in [20]. Briefly, the dataset contains raw ENG signals obtained from mechanical stimulations of the paw of three healthy Sprague Dawley rats. It includes signals from 16 channels detected by a multi-contact cuff electrode positioned on the sciatic nerve. The ENG signals have an amplitude of up to 50 µV and a main frequency band between 800 Hz and 2.5 kHz. These signals are generated through mechanical stimuli, alternating 3-second phases of exercise (dorsiflexion and plantarflexion) with phases of rest. The pre-processing pipeline applied to the signal is summarized in the flowchart in Fig. 2.

The compression algorithms have been implemented in Matlab R2023a and tested on a device with Intel(R) Core(TM) i7-9700K CPU @3.60GHz, 3600 MHz, 8 Cores, 8 Logical Processors and 16 GB of installed RAM. The operating system is a 64-bit system based on an x64 processor architecture.

A. *Quality Metrics*

In evaluating the seven compression algorithms implemented, various evaluation metrics were taken into account, which are detailed in [3, 4]. First, the **compression ratio** (CR), expressed as the ratio of the length of the uncompressed data to the compressed data, is used to quantify the size reduction obtained by the compression algorithm. The higher the parameter, the better the compression. It is possible that during the compression process the signal is deformed. The **Percent Root Difference** (PRD) must then be introduced to estimate the error in this process. Obtaining an accurate reconstruction of the signal from its compressed form is critical for subsequent signal classification. Therefore, the lower the value, the more efficient the compression will be. To ensure the delay introduced by the device during operation is imperceptible to the patient, the processes of signal acquisition, compression, and transmission must occur as quickly as possible (within a 300 ms threshold). Therefore, an important indicator for estimating the necessary time for these operations is the remaining time available for subsequent tasks performed by the device (signal processing, retransmission within the implanted device, and stimulation). This remaining time, known as **Residual Time**, is calculated as the difference between the 300 ms threshold and the time required for signal acquisition, compression, and transmission.

Finally, a new metrics was implemented, the **Log Spectral Distance** (LSD) [21]. This is a standard metric used to quantify the difference between the log spectra of the original and reconstructed signals. It is defined as the Euclidean norm of the difference between the log spectra of the original and reconstructed signals, providing a measure of spectral fidelity.

$$LSD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\log S_{x_i} - \log S_{\bar{x}_i}\right)^2} \quad (1)$$

Where N is the number of spectral samples, S_{x_i} is the spectrum of the original data, $S_{\bar{x}_i}$ is the spectrum of the reconstructed data. A higher LSD value indicates more distortion in the spectral content of the signal during the reconstruction process. This metric is crucial to evaluate how well the spectral characteristics of the original signal are preserved. Unlike other metrics such as PRD, which focus on discrepancies in the time domain, LSD provides a more nuanced view by focusing on deviations in the frequency domain.

B. *Optimization of compression parameters*

To analyze the compression algorithms, a preliminary investigation was conducted on the optimal parameters to perform the compressions. Time windows of 50 ms were used to proceed with the study. The parameters were evaluated based on CR and PRD quality metrics, trying to keep the PRD low while maximizing compression. The optimal values were determined by implementing the algorithms with different levels of compression and looking for the minimums or any plateaus of the metrics obtained.

For JPEG and JPEG 2000, the level (N) that guaranteed a CR of 1.5 and a PRD of less than 10% was N = 5. For FC, the box-counting method has been implemented to verify the fractality of the data. The angle value obtained was 0.98, close to 1, that indicates a fractal distribution [5]. Since the raw signal studied has a low signal-to-noise ratio, about 2, the algorithm has been retained. The optimal parameters chosen for compression were N = 1 with a package size of 200 samples, ensuring a CR of 7 and a PRD of less than 10%. For VQ, the codebook level chosen was 30, ensuring a CR of more than 7.5 and a PRD of less than 10%. LZW did not require the implementation of parameters, only the addition of a 100 µV offset, which was removed during decoding. For DPCM, a first-order linear predictor with a quantization level of 1.3 µV

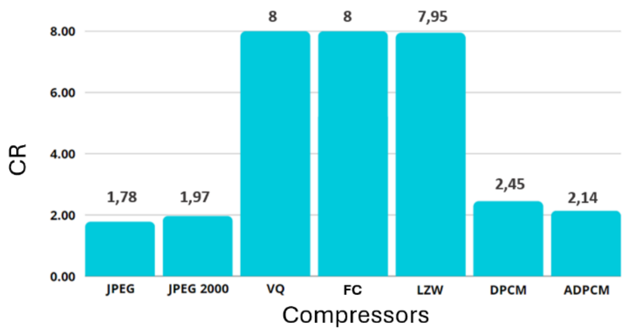

Figure 3 Offline compression (CR) results.

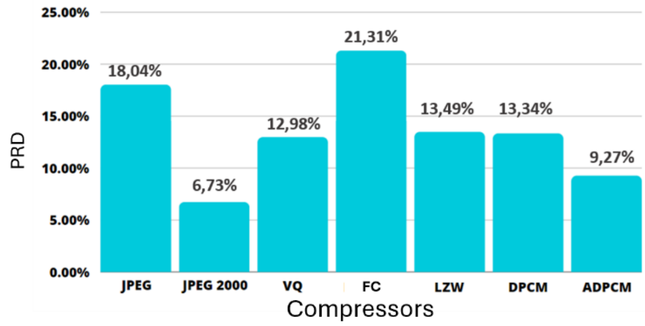

Figure 4 Offline compression (PRD) results.

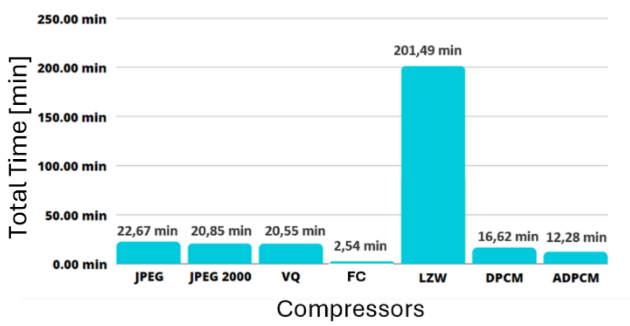

Figure 5 Offline compression results (total time).

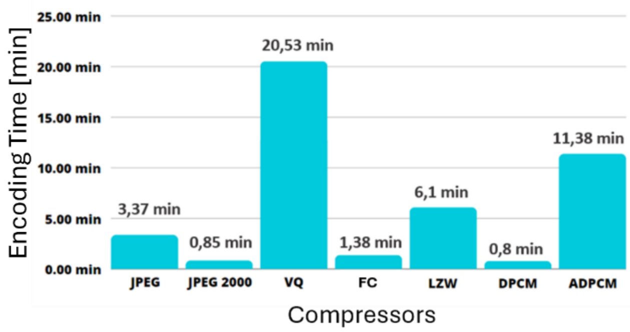

Figure 6 Offline compression results (encoding time).

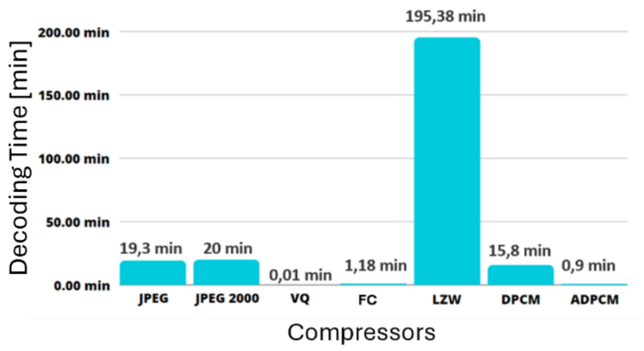

Figure 7 Offline compression results (decoding time).

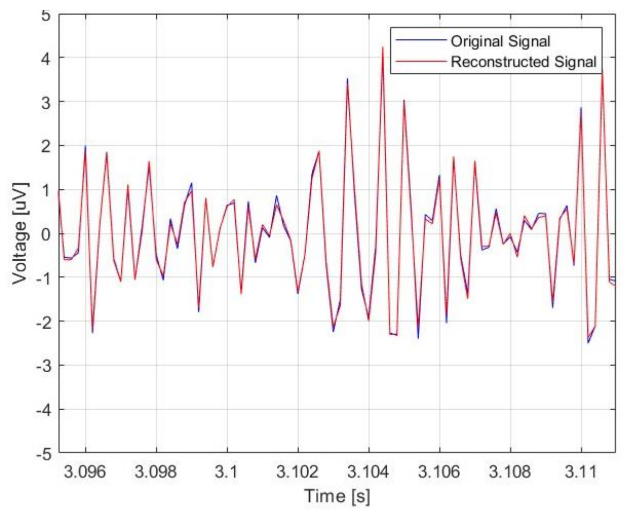

Figure 8 Time domain signal distortion after compression.

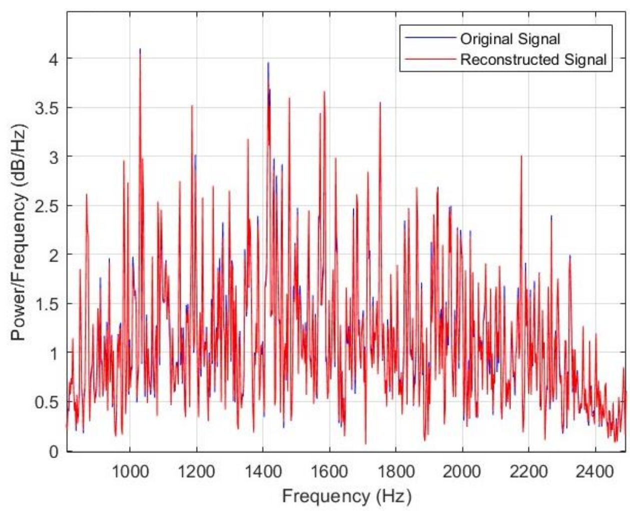

Figure 9 Frequency domain signal distortion after compression.

was used, resulting in a CR greater than 2 with a PRD below 10%. For ADPCM, a quantization grid of 30 was chosen, ensuring a CR greater than 2 with a PRD below 10%.

IV. Offline Approach, Results and Discussion

Once the parameters of the compression algorithms were defined, an offline approach was carried out to select which technique was the most suitable for a real-time application. In the offline approach, the entire ENG signal is compressed at the same time, regardless of any data transmission. 1-minute windows were used to derive the evaluation metrics. The algorithms were implemented one channel at a time, calculating the median of the results obtained from the three rats and both proprioceptive signals (+30° and -30°).

Figure 3 shows the CR values obtained after offline compression. The three best compression algorithms are VQ, HR with CR 8 and LZW with CR 7.95. On the other hand, the algorithm with the lowest CR is the JPEG with a CR of 1.78, which was then discarded in the online analysis for this reason.

As far as the reconstruction error estimated with the PRD is concerned, Figure 4, all algorithms respect a maximum limit of 30%, as indicated in [3]. On the other hand, there are some compressors that stand out for a particularly low PRD value, below 10%, namely JPEG 2000 and ADPCM with 6.73% and 9.27%. There are also three other algorithms with a good PRD value, below 15%: VQ, LZW and DPCM. Finally, the two worst algorithms when it comes to reconstruction error are JPEG and CF. Figure 8 is provided to illustrate the effects of distortion on the signal.

Regarding the evaluation of the algorithms' execution time, Figure 5, the total time was evaluated. This parameter is the sum of the encoding time, Figure 6, and the decoding time, Figure 7. In general, all algorithms have a rather high execution time (over 5 minutes) except fractal compression which is the fastest algorithm with a total time of less than 3 minutes. All other techniques have a total time of less than 25 minutes with the exception of LZW which requires a running time of 200 minutes. For this reason, LZW was discarded for online trials.

For the last parameter, Fig. 9, the LSD shows the distortions generated during the compression approach. According to [2] the main spectral component for the ENG signal is between 800-2500 Hz. For this reason, to do this analysis this frequency range was used in Eq. 1. The LSD value obtained is always below 0.025 for all the compression techniques tested. Because the value is relatively low, close to zero, indicates that the two signals (original and reconstructed) are very similar. This small difference suggests that the signal reconstruction has preserved the spectral characteristics of the original, with only slight variations. Considering the value achieved with LSD and PRD for both the characteristics spectral and temporal respectively were preserved and maintained during all the data compression methods.

Starting from the results obtained with the offline tests, four algorithms were selected to be tested with the online approach.

- The first to be selected is **VQ** as it is among those with the highest CR and has a good PRD (below 15%).
- The second algorithm is **FC**, with a CR equal to that of vector quantization and the only one among the methods implemented that allows compression and transmission of the entire signal in a time of less than three minutes.
- **JPEG 2000** was also selected as it was the technique with the lowest PRD of all.
- Finally, as far as predictors are concerned, the choice fell on the **DPCM**, as it achieves a higher CR than the ADPCM.

The selected techniques are able to preserve perfectly the characteristics of the ENG sigla.

V. Online Approach, Results and Discussion

In the online approach, the signal is divided into millisecond time windows to perform sequential compression. In this way, it is possible to compress data into smaller packets that can be transmitted to the outside via a communication system, such as BLE5. Various time window sizes were explored: 10 ms, 50 ms, 100 ms, 250 ms, and 500 ms. Prior to data compression, the signal was downsampled to 5 kHz to reduce computational weight.

The CR parameter was carefully evaluated for the four techniques. As shown in Figure 10, the two techniques VQ and FC stood out as the best with a CR of 8. Particular attention is paid to VQ, which manages to maintain this constant behavior even for the smallest windows. DPCM showed good CR values of about 2.5, although lower than the previous two. JPEG 2000, on the other hand, proved to be suboptimal, particularly for smaller windows.

As far as the PRD is concerned, the results are shown in Figure 11. All algorithms have a PRD of less than 15%, which is considered an acceptable value for subsequent signal classification. Among the algorithms, JPEG 2000 stands out as the most accurate maintaining a PRD of 5%. It is interesting to note that the FC, compared to the others that have a constant PRD value for each window, is the only one to have a different trend. For smaller windows, it can reduce the error by up to 9%, making it much more effective than other VQs and DPMS.

Finally, as far as redundancy time is concerned, this is maintained for all algorithms positive for time windows of less than 100 ms inclusive, Figure 12. Exception to JPEG 2000, for which the time interval must be less than 100 ms excluded to have a positive redundancy time. For this reason, for all algorithms, the optimal time window duration should be set between 10 ms and 50 ms to ensure a positive time.

A. Literature comparison

A comparison with the techniques implemented in [3] can be done. The three best techniques for ENG signal compression using traditional approach are found to be DCT + GZIP, DCT + ZLIB and DWT + ZLIB. The average CRs obtained are for DCT + GZIP about 1.67, DCT + ZLIB about 1.67 and DWT + ZLIB about 2.22. The results demonstrate that all the techniques we implemented, except JPEG 2000, offer higher CR performances. They are therefore more efficient for managing a large amount of data. As for the PRD, the average values obtained are DCT + GZIP about 7%, DCT + ZLIB about 7% and DWT + ZLIB about 15%. These results indicate that the two techniques using DCT are able to preserve data better than the other techniques presented. However, although the PRD is low, the CR value for these techniques is lower, therefore the compression is less efficient. Considering both metrics, our techniques are still superior for handling large amounts of data. A time comparison is not possible because different hardware was used for the compression implementation.

VI. Conclusion and Future Developments

Thanks to the results obtained from the online analysis, a general assessment of the performance of the algorithms can be provided. In particular, Table 1 shows the 4 algorithms from the best (1st column) to the worst (4th column) for each evaluation index.

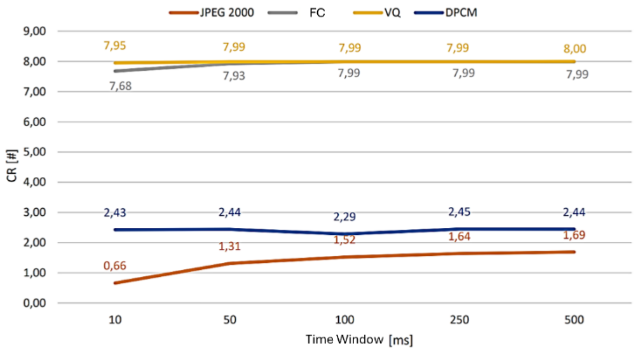

Figure 10 CR in online mode on 5 kHz ENG signal.

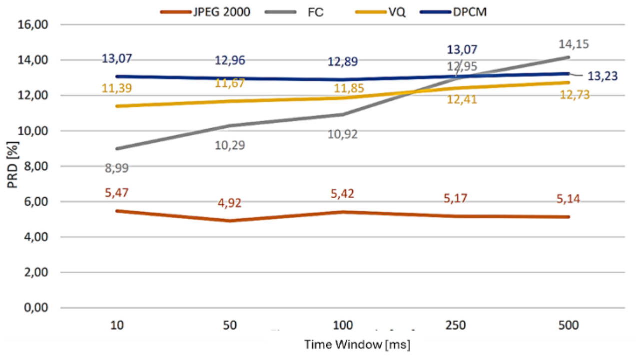

Figure 11 PRD in online mode on 5 kHz ENG signal.

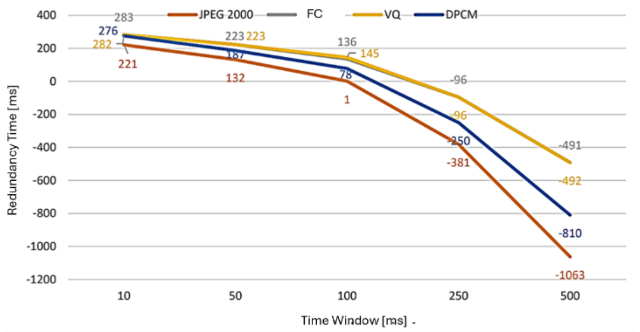

Figure 12 Transmission time in online mode on a 5 kHz ENG signal.

Table 1 Overall compression results.

Evaluation Metrics	1°	2°	3°	4°
CR	VQ	FC	DPCM	JPEG 2000
PRD	JPEG 2000	FC	VQ	DPCM
Redundancy Time	FC	VQ	DPCM	JPEG 2000

For the final evaluation, only time slots of less than 100 ms inclusive were considered. Windows with larger dimensions did not comply with the maximum time requirement below 300 ms [3] and were discarded as a result. Considering compliance with the minimum requirements, i.e. CR > 1, PRD < 15% and redundancy time > 0, the best algorithms were identified among those implemented. In particular, considering these three key parameters together, the two best performing compressors are **FC** and **VQ**. Both maintained good levels of near-constant PRD across all time windows, ensuring a high CR. DPCM showed good performance but still inferior to the first two mentioned, both for CR and redundancy time. As far as the PRD is concerned, on the other hand, it obtained higher values, remaining below 15%. On the other hand, JPEG 2000 while ensuring very low error, has generally emerged as the worst algorithm due to the significantly lower CR and redundancy time compared to all the others.

Ultimately, we can therefore say that the analysis conducted opens promising avenues for future research in the field of neural bypass. Particularly for real-time application, the most effective compression algorithms were FC and VQ, with DPCM showing good performance, although slightly lower than the other two. The algorithms could be implemented on implanted devices and used to facilitate real-time communication. An interesting future development concerns the effects of compression in the classification of the ENG signal. A preliminary study was conducted using the ENGNet network [2] to assess its effects. We found a maximum performance mean accuracy (and F1-score) reduction of 0.1% (0.5%) in case of 50ms window compression and 1% (1%) in case of 10ms window compression. The classification performances have been evaluated for the compression algorithms implemented in [3] and those developed in this paper. We can therefore say that, as long as a good level of PRD is guaranteed, the compression has no effect on the classification of the ENG signal. This further confirms that these algorithms can actually be used for real-time applications.

VII. Bibliografy

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