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An Evaluation of the Effects of Wavelet Coefficient Quantization in Transform Based EEG Compression

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Abstract

In recent years, there has been a growing interest in the compression of electroencephalographic (EEG) signals for telemedical and ambulatory EEG applications. Data compression is an important factor in these applications as a means of reducing the amount of data required for transmission. Allowing for a carefully controlled level of loss in the compression method can provide significant gains in data compression. Quantization is an easy to implement method of data reduction that requires little power expenditure. However, it is a relatively simple, noninvertible operation, and reducing the bit-level too far can result in the loss of too much information to reproduce the original signal to an appropriate fidelity. Other lossy compression methods allow for finer control over compression parameters, generally relying on discarding signal components the coder deems insignificant. SPIHT is a state of the art signal compression method based on the Discrete Wavelet Transform (DWT), originally designed for images but highly regarded as a general means of data compression. This paper compares the approaches of compression by changing the quantization level of the DWT coefficients in SPIHT, with the standard thresholding method used in SPIHT, to evaluate the effects of each on EEG signals. The combination of increasing quantization and the use of SPIHT as an entropy encoder has been shown to provide significantly improved results over using the standard SPIHT algorithm alone.

Keywords

EEG; Compression; SPIHT; Quantization; AEEG; Telemedicine

1 Introduction

Electroencephalography (EEG) has long been used as a tool in clinical settings for diagnosing a variety of neurological and physiological conditions. It involves measuring a person’s neural activity by placing electrodes on the scalp and detecting the bio-electric

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Conflict of Interest

None Declared

activity caused by synchronised neuronal activity within the brain. Typically this is performed as an in-patient procedure, whereby the patient is monitored for an extended period of time in a clinical setting. This places the patient in a potentially unfamiliar environment which may cause anxiety or stress, and removes them from their natural environment, which may contain triggers for certain conditions. As an in-patient procedure, it also consumes clinical resources, which ultimately costs the health service in staff time and money.

One of the most common uses of EEG as a clinical tool is in the diagnosis of epilepsy. Epilepsy is a neurological condition that affects approximately 1% of the population [1], [2], but is difficult to diagnose. The gold-standard diagnosis requires long-term EEG and video monitoring in an attempt to capture a seizure on both video and EEG telemetry [3]. However, there is still a chance that no epileptiform activity will be experienced within the period of evaluation. Although accurate figures for the general population are difficult to determine, one study has shown that for EEGs taken from 308 patients with epilepsy, 18% never exhibited epileptiform discharges over several months of recordings and only 55% displayed discharges during their first examination [4]. It is conceivable therefore, that a patient displaying potential signs of epilepsy, may display no seizure activity during a single in-patient monitoring session.

Misdiagnosis is also a significant issue due to limitations in the data available to the clinician. Smith *et al.* [5] reports that elongating the period of EEG observation would have the effect of reducing the number of false positives, and increasing the detection rate of epileptiform activity. Binnie *et al*. [6] report that long-term monitoring may be required in as many as 5% of people diagnosed with epilepsy, and 13–20% of adult tertiary referrals and up to 40% of child referrals with potential cases of epilepsy. Clearly, in these situations, long-term in-patient monitoring is less than ideal in terms of expense, resource allocation and patient inconvenience. This situation is exacerbated where the availability of trained clinicians with the skills to analyse long term EEG data for seizure activity is limited.

Recent years have seen an increased interest in Ambulatory EEG (AEEG) devices and telemedical applications [7]–[12]. In a recent survey of 17 neurologists in the UK, 88% said they thought AEEG recordings would be more common in the future, and 76% said it would be a "major improvement" to their practice if AEEG devices were available [8]. Although AEEG devices have been in existence since the 1960s [13], [14], improvements in the efficiency of signal processing techniques, combined with increased capacity in modern batteries have made a practical implementation more feasible. Wireless communication however, still remains proportionally one of the largest consumers of power in the system [15]. For patients in remote areas, it can be problematic to provide skilled clinicians to analyse data. Telemedical systems can provide a means to monitor and diagnose potential epilepsy sufferers from remote locations [16]–[18]. Using an AEEG or remote EEG monitoring system would alleviate the demands placed on finite resources by allowing clinicians to review the data at their convenience, or use automated seizure detection to assist with diagnosis. Remote rural locations where these systems can be of the greatest benefit, are rarely serviced with high speed network connectivity, therefore attempting to

transmit the raw, uncompressed signal is impractical. Any reduction in the quantity of the data to be transmitted would be a benefit.

In general, there are 2 types of data compression: lossless and lossy. Lossless compression maintains signal integrity while compressing and decompressing the data, but is generally severely limited in the Compression Ratio (CR) it can achieve. Currently the majority of EEG compression research focuses on this method. Lossy compression results in an imperfect representation of the original signal, because signal fidelity varies according to the parameters of the compression method. By allowing a measure of loss to be tolerated, far higher compression levels can be achieved. Careful selection of compression parameters can maximise CR while minimising the loss of important information contained within the signal.

This paper aims to examine the effects of compression by comparing two lossy approaches:

- Set Partitioning in Hierarchical Trees (SPIHT) compression, with loss introduced through SPIHT's thresholding and embedded encoding features
- Progressive lossy quantization of the wavelet coefficients with SPIHT being employed losslessly as an entropy encoder

Both schemes can provide a wide range of compression ratios. This paper examines the impact of quantization’s rounding method as opposed to SPIHT’s coefficient thresholding method as factors of compression in order to maximise compression gains.

The rest of the paper is arranged as follows: Section 2 outlines the research methodology used in this work and how this work fits into EEG compression research. The dataset used is described and the data compression algorithms are outlined. Additionally, the metrics used for evaluating the results are given. Section 3 presents the results obtained from the compression tests. Section 4 analyses these results and evaluates the validity of the conclusions reached from them, and compares the results found here with results from similar research elsewhere. Section 5 gives the conclusions of the paper and proposes potential future work.

2 Research Methodology

2.1 Epileptiform EEG Database

The epileptiform EEG data used in this research was provided as part of the Seizure Prediction Project by the University of Freiburg, Germany [19]. The database contains EEG data recorded during pre-surgical monitoring. It contains seizure and non-seizure data for 21 patients ranging in age from 13 to 50. The dataset was chosen due to its public availability and to limit the number of artefacts present due to recordings being made through intracranial electrodes. The 6-channel EEG used in the recordings, is similar to the number of channels likely to be used in an AEEG device [20].

2.2 Compression

3.2.1 Background—Biomedical signal compression techniques can be broadly divided into three categories: 1) Direct Data 2) Transform based compression and 3) Other compression methods [21], [22]. Direct Data methods are generally time domain based approach that exploits redundancies in signal data to increase compression. Compression efficiency is therefore limited by the fact that EEG is not sparse in the time domain. Memon *et al.* present an evaluation of a number of direct data compression techniques in [23]. In it they note that traditional direct data techniques do not work well on EEG signals due to the lack of reoccurring, exact patterns.

Methods in category 3) include compression methods such as non-linear prediction, neural network based compression and subband coding (other than those used in transform based approaches). Sriraam *et al.* present a number of recent papers on EEG compression using neural networks [24], [25]. In both papers, the authors make use of predictors as part of an approach to give near-lossless compression of EEG data. This is combined with quantization and entropy encoding schemes to maximise compression gains. In [26], Bazán-Prieto *et al.* present an EEG compression technique based on cosine modulated filter banks, with 7 bit quantization. They test their algorithm on two EEG databases; the CHB-MIT Scalp EEG Database and the MIT-BIH Polysomnographic Database [27]. It is noted in [22] that despite the similarity between the subband decomposition employed by their algorithm and those frequently employed by transform based compression, it is not in actuality a transform method.

Transform-based compression includes methods that transform the time domain signal into the frequency, or other domain prior to compression. Examples of these transform operations include the Fourier Transform (FT) and Wavelet Transform (WT) which exploit signal sparsity in a particular domain [28], [29]. The research presented by Cárdenas-Barrera *et al.* in [28] is an important paper in the field of EEG compression. It is the first paper to propose an upper limit to the level of fidelity loss allowable in EEG compression, based on retaining the majority of the signals energy. In this work they examine lossy compression approaches based on wavelet and wavelet packet transforms using the MIT-BIH Polysomnographic Database [27]. In [30], Daou and Labeau present a 2-D SPIHT based EEG compression methodology using EEG data obtained from Montreal Neurological Institute. They propose a pre-processing technique to exploit the correlation between EEG channels to maximise compression and employs two transform operations: a DWT and Discrete Cosine Transform (DCT).

The research presented in the present paper falls into category 2). This paper contributes to the area of transform-based encoding by evaluating the impact of reduced quantization bit-rates on DWT coefficients, prior to entropy encoding. Section 4.2 provides a comparison between the results of this algorithm and other works of lossy EEG compression.

3.2.2 Discrete Wavelet Transform (DWT)—This section provides a brief overview of the DWT which is employed as a pre-processing step to the compression approaches investigated in this paper. DWT is commonly used in compression algorithms due to its ability to represent signals in both the time and frequency domain. The DWT decomposes a

signal into a set of basis functions known as wavelets [31], [32]. The initial wavelet, also known as the mother wavelet (ψ), is used to construct the other wavelets by means of dilation and shifting. Dilation is achieved by multiplying the function's time orientation *n* by a scaling factor 2^m, where $m \in Z$. Shifting in time is done by $k \in Z$.

Therefore, the wavelet decomposition is defined by:

$$x(n)=\sum_m\sum_k c_{m,k}(\psi(2^m n-k)), m,k \in Z \quad (1)$$

where the scale *m* relates to the wavelet's dilation. Basis functions associated with large scales extract low-frequency information from the signal, while small scales extract high-frequency or fine-detail components. The DWT coefficients $c_{m,k}$ are defined as the inner product of the original signal and the selected basis functions:

$$c_{m,k}=<x(n),\psi_{m,k}(n)> \quad (2)$$

These coefficients provide an alternative representation of the original signal, giving good localisation of the signal's energy components from both a time and frequency perspective. In this application the CDF 9/7 biorthogonal DWT was used [33], [34] at a 10 level decomposition. This mother wavelet was chosen due to its widespread use in compression research, including SPIHT compression of biomedical signals [35]. The high level of wavelet decomposition extracts the dominant low frequency components of the signal. This improves SPIHTs compression efficiency by allowing the construction of "higher" zero trees while encoding. This ability to construct large zero trees is in agreement with empirical results which reveal that a 10 level decomposition provides best compression gains and reconstruction capability, with low levels of fidelity loss.

3.2.3 Quantization—Quantization is a nonlinear and noninvertible method of mapping a large, finite sequence of numbers, $x(n)$, onto a smaller scale, $x(\hat{n})$. Quantization occurs in digital signal processing where signals are sampled and converted into a digital format. The range $x(n)$ is divided into a number of equal intervals and then each interval is mapped to a codeword. It is worth noting that the codeword refers only to the interval and not to the original value. All input values are then expressed in terms of the interval they fall between.

The decoding process attempts to convert the $x(\hat{n})$ sequence back to the original scale. However, due to the codeword referring to the interval only, the decoder can not know the exact value of the original signal. For this reason, the decoded sequence, $x'(n)$, will not be an exact reconstruction of the original sequence, $x(n)$. The larger the number of intervals, the closer the decoded sequence will be to the original. However, with a smaller number of intervals, the number of bits needed to represent the encoded sequence diminishes. The quantization bit-rates used in this paper ranged from 1 to 16 bits. 16 bits was chosen as the highest resolution as it is the quantization level used during the raw capture of the EEG signals. Quantization was performed on the wavelet coefficients in order to reduce the range of the coefficients being passed to the SPIHT encoder.

3.2.4 Set Partitioning in Hierarchical Trees—Initially proposed by Said and Pearlman in [36], Set Partitioning in Hierarchical Trees (SPIHT) is a compression method originally designed for image compression that has since been applied to many other application areas [35], [37], [38]. Its core principles are derived from the Embedded Zerotree Wavelet (EZW) coder proposed by Shapiro in [39] by exploiting the fact that wavelet coefficients in different sub-bands have a temporal relationship with one another. As with the EZW algorithm, SPIHT arranges the bits in order of significance, with the most significant bits being encoded first. Therefore, if the encoding or transmission is interrupted at any point, the signal can be reconstructed to a level of fidelity appropriate to the number of bits received. This means that SPIHT allows for direct control of the CR of the signal being encoded.

In this paper, the data was compressed with CRs from the set c = {1, 2, 5, 6, 7, 10, 30, 35, 40, 55, 110, 160, 200}. For c = 1, SPIHT operates in a lossless manner, where the input sequence prior to compression is identical to the output sequence after the data has been decompressed. When SPIHT operates at CRs higher than this, it compresses the signal by discarding all coefficients below the selected threshold. For example, for c = 4, only 25% of the original bit length is saved.

3.2.5 Approaches to Compression—The DWT, Quantization and SPIHT components were used to test different approaches to lossy compression. Compression involves the original signals undergoing a DWT operation followed by Quantization, before being encoded using SPIHT. Two different variations in this methodology were used: First, the traditional SPIHT approach where the desired CR was selected prior to compression and was achieved by terminating encoding at the desired bit-length. For this approach, the quantization level of the DWT coefficients was set at 16 bits. This was done to isolate the compressive effects to that of SPIHT's bit-ordering/discarding. This approach was dubbed "Standard SPIHT". In the second approach, the number of bits available to the quantizer was varied and the resulting coefficients encoded by SPIHT in lossless mode. In this approach, SPIHT was used as an entropy coder to gain maximum compressive gains from the lower bit-rates. This approach was taken to isolate the effects of varying the quantization level in order to examine its specific effects. This approach was dubbed "QSPIHT"

2.3 Performance Metrics

Two performance metrics were used for evaluating the performance of the compression algorithms.

- **Percentage Root-mean squared Distortion (PRD)** is a standard metric for measuring the distortion between 2 signals. It is defined as:

$$\mathrm{PRD}=\left(\frac{\|x-\hat{x}\|}{\|x-\bar{x}\|}\right)\times 100 \quad (3)$$

where x is the original signal, $\hat{x}$ is the reconstructed signal, $\bar{x}$ is the mean of the signal and $\|.\|$ represents the Euclidean and l^2 norm.

Previous research has already investigated the effects of PRD on EEG signals and proposed limits to ensure no impact on diagnostically relevant information. Cárdenas- Barrera *et al.* proposes a PRD limit of 7% to ensure 99.5% of the signals energy is retained [28]. Higgins *et al.* however, determined that a much higher PRD (30%) can be tolerated while still maintaining seizure information [40], [41]. This is further verified in [29] where an automated seizure detection algorithm is used to verify these PRD limits. These 7% and 30% PRD limits were chosen as the operating points in this research to provide a reference point for potential real-world applications such as clinical review and automated seizure detection.

- **Compression Ratio (CR)** is defined as the ratio of the size of the compressed signal in relation to that of the original signal, and is given by the formula:

$$\mathrm{CR}=\frac{L.r}{\hat{b}} \quad (4)$$

where L is the length of the input signal in samples, r is the original quantization (bit resolution) of each original sample and $\hat{b}$ is the number of bits representing the compressed signal.

In order to determine the CRs of the compression methods, the overall length of the compressed databases was used. The cumulative number of bits for each frame was recorded and the total number of bits for the whole database was compared to the size of the uncompressed data to give a true CR for each compression method.

Two further metrics were used to evaluate the validity of the compression results:

- The **Power Spectral Density (PSD)** is a method of analysing the contribution of each frequency to the overall signal power. It describes how the power of a time series is distributed with frequency. The PSD of the signals after compression were plotted against the PSD of the original signals to evaluate the impact of the lossy compression on the energy of the signal. For this research the Welch method of PSD estimation was applied to the signals being analysed [42]. A segment length of 64 with a 50% overlap using the Hamming windowing method and 64 length window was used.

Finally, the **Cumulative Density Function (CDF)** is a measure of probability distribution of a random variable. Given a continuous random variable X, the CDF is denoted as a function $F(x)$, and is defined for a number x by:

$$F(x)=P(X\leq x)=\int_{0}^{x} f(s)ds \quad (5)$$

That is, for a given value x, $F(x)$ gives the probability that observed value of X will be less than or equal to x. The CDF was used to examine the likelihood of a compressed frame

having a PRD at or below a specific value when the given compression parameters are applied.

Unlike other bioelectric signals, such as ECG [43], no metric exists to evaluate fidelity loss in EEG signals in regards diagnostically relevant information. PRD was chosen for this research due to its widespread use to analyse quality degradation in lossy EEG compression ([26], [28], [29]). In this research, PSD analysis is added to verify the results inferred by the PRD values.

3 Results

3.1 Standard SPIHT Compression

For this approach, the quantization level was fixed at 16 bits. The signals were compressed with SPIHT at a range of lossy compression settings, ranging from CRs of 2 to 200, and then decompressed. The PRD of each frame was calculated and then the mean and standard deviation over the whole database was determined. Table 1 presents the results of this work. It can be seen that at the lowest compression level (CR = 2), the PRDs are very small, suggesting an insignificant loss in fidelity between the original and reconstructed signal.

As previously stated, two PRD limits are proposed for use in this research. The 7% and 30% limits were used as lower and higher cut-off points for seizure detection applications [28], [40], [41]. These limits were therefore selected as operating points for comparative reasons. It can be seen from Table 1 that a CR setting of 5 (CR5) gives a PRD of 5.99%, which lies within the 7% cut-off limit. Looking at the 30% limit, it can be seen that a CR setting of 35 (CR35) gives a PRD of 29.26%.

The final column gives the standard deviation of the PRD results. At the proposed settings, the standard deviation is ±6.18 and ±18.85 respectively. This suggests that while the average PRD results fall within the limits, it is obvious that some frames can be well above the desired limits. Further analysis of these results is therefore required and is provided in Section 4.1 of this paper.

3.2 QSPIHT Compression

For this section, the database was compressed by quantizing the data in the range of 1 to 15 bits, and compressed using SPIHT in lossless mode. Table 2 gives the CRs for the database after SPIHT compression has been applied. The PRD values were recorded for each frame and then averaged over the whole database at each quantization level. Table 2 gives the average PRD and standard deviation at each bit-rate.

Looking at the results, it can be seen that while the PRD initially increases slowly, the rate of increase gets larger as the quantization level approaches 1 bit. Taking the initial 7% PRD limit, it can be seen that at 7 bit quantization (Q7) the PRD is 6.09%. For the 30% PRD limit, far lower quantization levels can be tolerated. In this situation, 4 bit quantization (Q4) is required to bring it below the 30% cut-off point, giving an average PRD of 23.66%.

Again the standard deviation is given in the last column of the table. For the suggested limits of 7% and 30% PRD is ±7.00 and ±13.88 respectively. Further analysis of the distribution of the results is therefore required and provided in Section 4.1 of this paper.

3.3 Comparison

In order to evaluate the performance of each approach, it is necessary to look at the PRD achieved by each at any given CR. Fig. 1 gives a plot of the CR vs. PRD for both methods. While the CRs for the standard SPIHT approach are known prior to compression, the exact CRs for the QSPIHT approach can only be determined after compression has taken place. Fig. 2 gives a magnified view of Fig. 1 from 0% to 10% PRD. Looking at Fig. 2 it can be seen that both approaches initially have very similar PRD and CR values. This is to be expected as at this point both approaches have little loss in signal fidelity, keeping CRs low. As the compression rate increases, the curves diverge. It is clear from the graph that QSPIHT out-performs Standard SPIHT compression in terms of PRD at a given CR. While the largest gains are at the higher CRs, these results fall outside the upper limits of loss imposed and are therefore irrelevant in the context of this research. Below the 30% limit, the QSPIHT approach still provides an advantage. At 30% PRD, the QSPIHT approach gives a CR of just over 100, while the Standard SPIHT approach gives a CR of approximately 40.

Within the 7% PRD limit, the advantage of the quantization approach is still substantial. The 7 bit quantization limit, found in the above section to fall below this cut-off point, gives a CR of 13.05. At 7% PRD, Standard SPIHT gives a CR of approximately 6.

4 Further Evaluation of Validity of Results

4.1 Analysis

In order to analyse the distribution of the PRD results at the proposed compression settings, the Cumulative Density Function (CDF) for the resulting frames was calculated and plotted. Fig. 3 shows the CDF of the QSPIHT and Standard SPIHT approaches at Q7 and CR5 respectively for the 7% PRD limit. Looking at Fig. 3 it can be seen that the CDF of both approaches are very similar. Both rise rapidly until the probability goes above 0.9, where a shallower increase can be observed. This is to be expected as the (relatively) low compression settings maintain most of the signal fidelity. Examining the 7% PRD ($x = 7$), it can be seen that the probability of a given frame having a PRD of 7% or less for both approaches is 0.8 or 80%.

Fig. 4 shows the CDF of both algorithms at the proposed 30% PRD settings (Q4 and CR35). Again both CDFs follow a similar distribution. Standard SPIHT starts higher than QSPIHT, implying a higher proportion of frames with PRDs below 10%. Above this however, QSPIHT rises faster than Standard SPIHT, implying the QSPIHT approach gives lower PRDs than Standard SPIHT in this range. At 30% PRD ($x = 30$) there is a 0.8 or 80% chance for QSPIHT and approximately 0.75 or 75% chance for Standard SPIHT that a given frame will have a PRD equal to or lower than the cut-off.

Since PRD is a measure of the level of difference between two signals, and not by definition an objective evaluation of the impact of the loss of diagnostically relevant information in the

signal, it should not be used as the sole metric to evaluate the performance of the algorithms. To do this, a visual inspection and PSD analysis was performed on a selection of reconstructed files whose PRDs were close to the above limits. Figs. 5 and 6 give the PSDs of original signal and those of the QSPIHT and Standard SPIHT approaches at the 30% and 7% cut-off PRDs, given in Plots (i–ii) in each Figure. Fig. 5 is a randomly chosen EEG signals containing no seizure information, while Fig. 6 was chosen to contain periods of seizure data. The parameters found to give optimum results in the section above were used to select the signals for comparison. Specifically, these were CR35 and Q4 at 30% PRD and CR5 and Q7 at 7% PRD for Standard SPIHT and QSPIHT respectively. Performance was judged on how closely the PSD of the reconstructed signals visually matched that of the original signal, i.e. how well the energy is maintained in the signal after lossy compression.

Generally all 4 reconstructed signals maintain a PSD close to that of the original signal, particularly in the case of the low PRD signals. Fig. 5 shows the greatest amount of variation in the signals PSDs with all PSDs being very similar in Figs. 6. Plot (i) shows Standard SPIHT at CR35. The greatest variation in original and reconstructed signals PSDs can be seen here, with the reconstructed signals power being generally slightly lower than the original. Plot (i) also shows QSPIHT at Q4. Here the PSD is closer to that of the original signal, although some variation is still visible. Plot (ii) shows Standard SPIHT at CR5. Again an improvement can be seen in the reconstructed signals PSD but some loss in fidelity is still evident. Finally, Plot (ii) also displays QSPIHT at Q7. Here almost no variation in PSD between the original and reconstructed signals is visible, suggesting almost no loss in signal information during compression.

A visual inspection was also performed on the signals. Fig. 7 shows a sample of the database with (i) the original EEG signal, and the signal compressed with (ii) QSPIHT at Q4 and (iii) Standard SPIHT at CR5. This signal gives CRs of 10 and 5 and PRDs of 3 and 2 respectively. Visually, these three signals are nearly identical, suggesting very high retention of signal integrity. Fig. 8 shows a plot of (i) the same original EEG signal, and the corresponding sample compressed with (ii) QSPIHT at Q4 and (iii) Standard SPIHT at CR35. At these settings, these algortihms give a CR of 42 and 35 and PRD of 14% and 17% respectively. At this higher level of loss, some visual discrepancies can be seen. These higher levels of compression cause a smoothing effect on the signals due to the loss of finer detail coefficients. While some of the finer details are lost in the compression, the general shape of the signal is very well maintained. This again suggests the majority of the signal information is maintained at this compression level.

The similarities, visually and in the PSDs, of the original and reconstructed signals after compression lends credence to the choice of the 7% and 30% PRDs as operating points, as most of the signals power is preserved at each compression level. When QSPIHTs superior PSD results are combined with the compression results from Sections 3.1 and 3.2 above, a clear advantage in increasing quantization level to improve CR performance can be seen.

4.2 Comparison with Other Work

A direct comparison with other EEG compression research is difficult due to the variety of EEG databases and performance evaluation metrics used. In comparison to other biomedical

signal research, there is a relatively small amount of research being done in the area of EEG compression. In order to address some of these difficulties, a publicly available EEG database was selected for testing [19] and results were reported using the PRD metric given in (3) as it is not influenced by the signal mean. It is possible to make general comparisons when CR and PRD results are reported by comparing with those of Fig. 1. It should be noted that an alternative definition of PRD, employed by [24], [28], [30], does not remove the signal mean prior to calculation. This inclusion of the mean (DC bias) can create an artificially low PRD, whereby the mean of the signal is maintained, while important signal information is lost. Without adjusting for the signal mean in PRD calculations, the results can be up to 4 times better (lower PRD for a given CR) than if the definition employed in this paper is used [26]. In the case of [26] and [28], QSPIHT was applied to the same databases to aid comparison. Table 3 gives the results of QSPIHT run on these databases for bit-levels 4 to 9.

For transform based compression, Cárdenas-Barrera reported an average PRD of 9.54% and CR of 7.79; while at 7 bit quantization the average CR is 5.68 with an average PRD of 6.02% in [28]. Table 3 gives the corresponding results for QSPIHT. The database used was the MIT-BIH Polysomnographic database. At Q7, a CR of 9.5 at a PRD of 6.93% is achieved. It is interesting to note the advantage of using SPIHT as an entropy encoder, increasing the CRs from 7.79 to 13.021 and 5.68 to 9.5024 for 6 and 7 bit quantization respectively.

Daou and Labeau present a 2-D SPIHT based EEG compression methodology in [30]. Improved compression performance in comparison to 1-D SPIHT and a number of other algorithms were reported for PRDs lower than 30%. The results found here suggest that the addition of a quantization block, with an appropriate bit-level, prior to SPIHT encoding may provide improved compression results with minimal impact on fidelity.

An alternative approach to compression is presented in [26]. Bazán-Prieto *et al.* report achieving a CR of 5.97 at 4.61% PRD and 11.23 CR at 10.45% PRD for the CHB-MIT database. On the same database, QSPIHT gave a CR of 5.33 at 3.08% PRD and 13.42 CR at 10% PRD. This was achieved at Q7 and Q5 respectively. For the MIT-BIH Polysomnographic database, a CR of 4.11 is reported at 3.79% PRD and 8.21 CR at 10.26% PRD. QSPIHT achieved a CR of 3.73 at a 2.54% PRD and 13.02 CR at 11.81% PRD. This was achieved at Q9 and Q6 respectively.

In [24], Sriraam reports CRs of approximately 5:1 with PRDs no higher than 5%, using a proprietary database. This result is similar to those of the Standard SPIHT approach used here, where CR and PRD have a close to linear relationship. QSPIHT may offer improvements on these results.

5 Summary and Conclusions

This paper has examined two methods of EEG compression based on reducing data length by: (i) ordering the coefficients into hierarchical trees and then discarding those that fall below the threshold value and (ii) rounding coefficients to integer values using varying

levels of quantization and losslessly compressing them. This was done by applying the SPIHT algorithm at a variety of compression levels in the first approach and varying the quantization level for the second. Two limits of signal loss were used to evaluate the compression algorithms performance against each other in relation to real-world applications. It was found that (ii) achieved higher CRs at a given PRD than (i). At a 7% PRD, (ii) achieved a CR of 13.05 while (i) achieved 6. At 30% PRD, (ii) achieved a CR of 100 compared to 40 with (i). The validity of these results was evaluated by comparing the information contained in the signals after they had been decompressed, with that of the original signal. It was found that the reconstructed signals maintain the energy spectrum of the original signal well, particularly at low PRDs. Furthermore, it was found that the PSD of data compressed using (ii) was closer to that of the original signals than (i). This suggests that (ii) achieves higher CRs than (i) while maintaining better data fidelity. Thus, it appears to be more beneficial to the integrity of the EEG data to use a compression method that represents all signal coefficients, even in a reduced form, rather than one that simply discards coefficients.

This work may be extended by applying the results found here to the design of an EEG compression algorithm that makes use of higher quantization levels as the basis of compression. Combining higher quantization levels with other methods of data compression may offer a means of further increasing CRs without undue impact on the EEG signals. While SPIHT is used here in lossless mode, the results may be improved by combining higher quantization levels, with a measure of lossy compression. Alternatively, a coder other than SPIHT could be used post quantization if a requirement such as ultra-low power consumption is required. Furthermore, the quantization method used here was a standard, uniform quantization method. Implementing a more advanced quantization method may yield higher CRs or improve signal integrity at a given CR.

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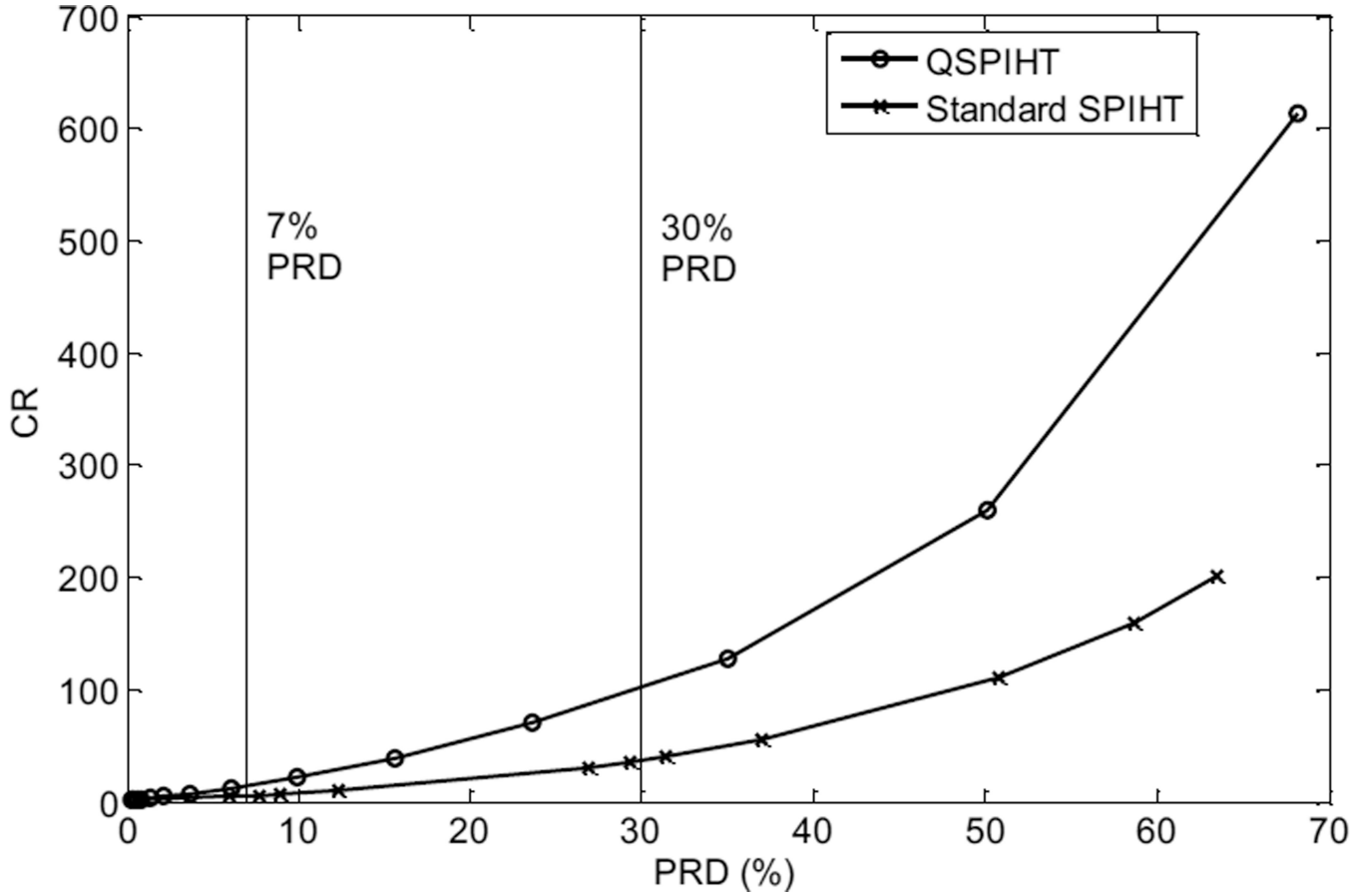

Figure 1.
Plot of PRD vs. CR for Standard and QSPIHT approach

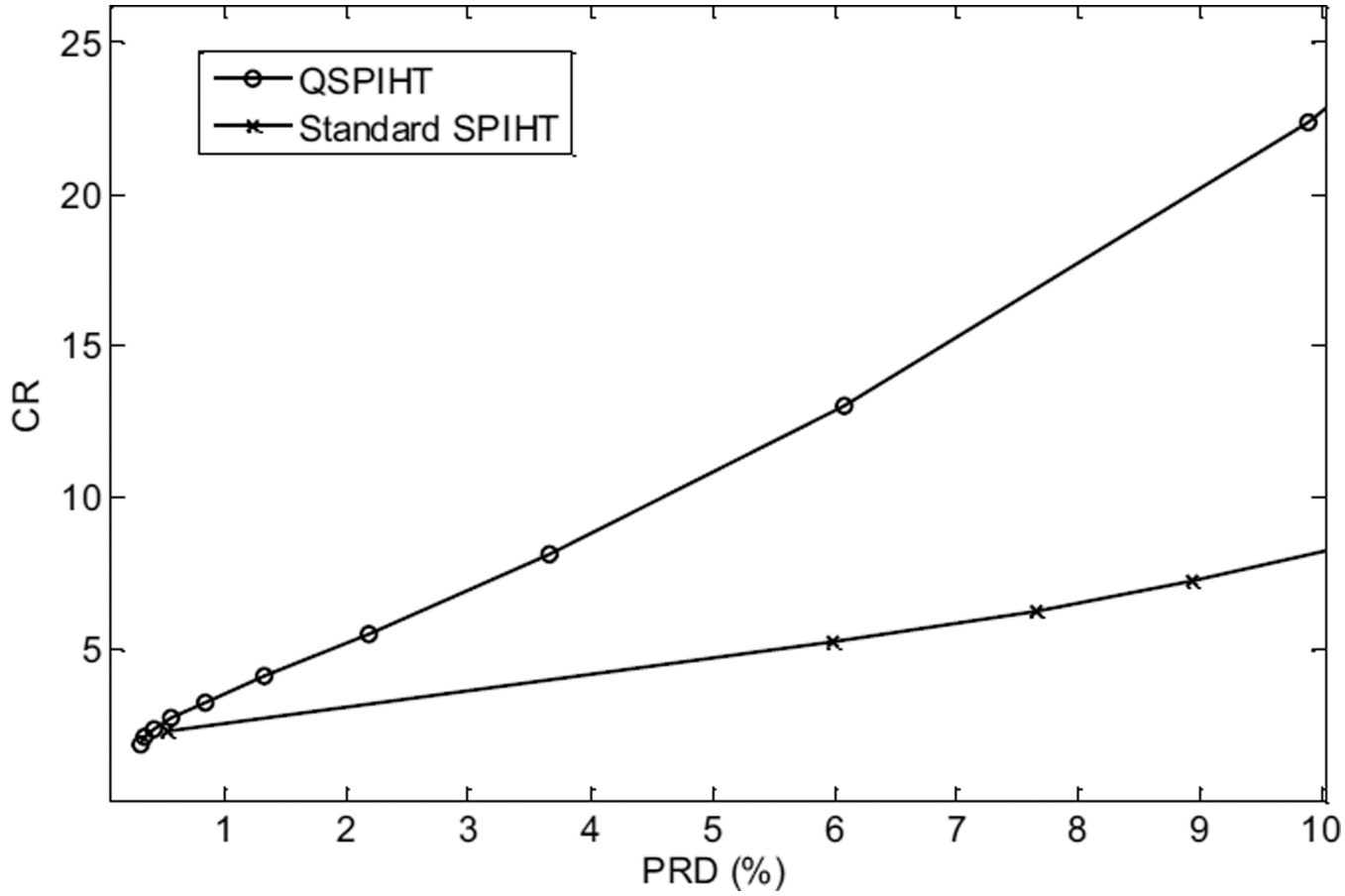

Figure 2.
Plot of PRD vs. CR for PRDs up to 10%

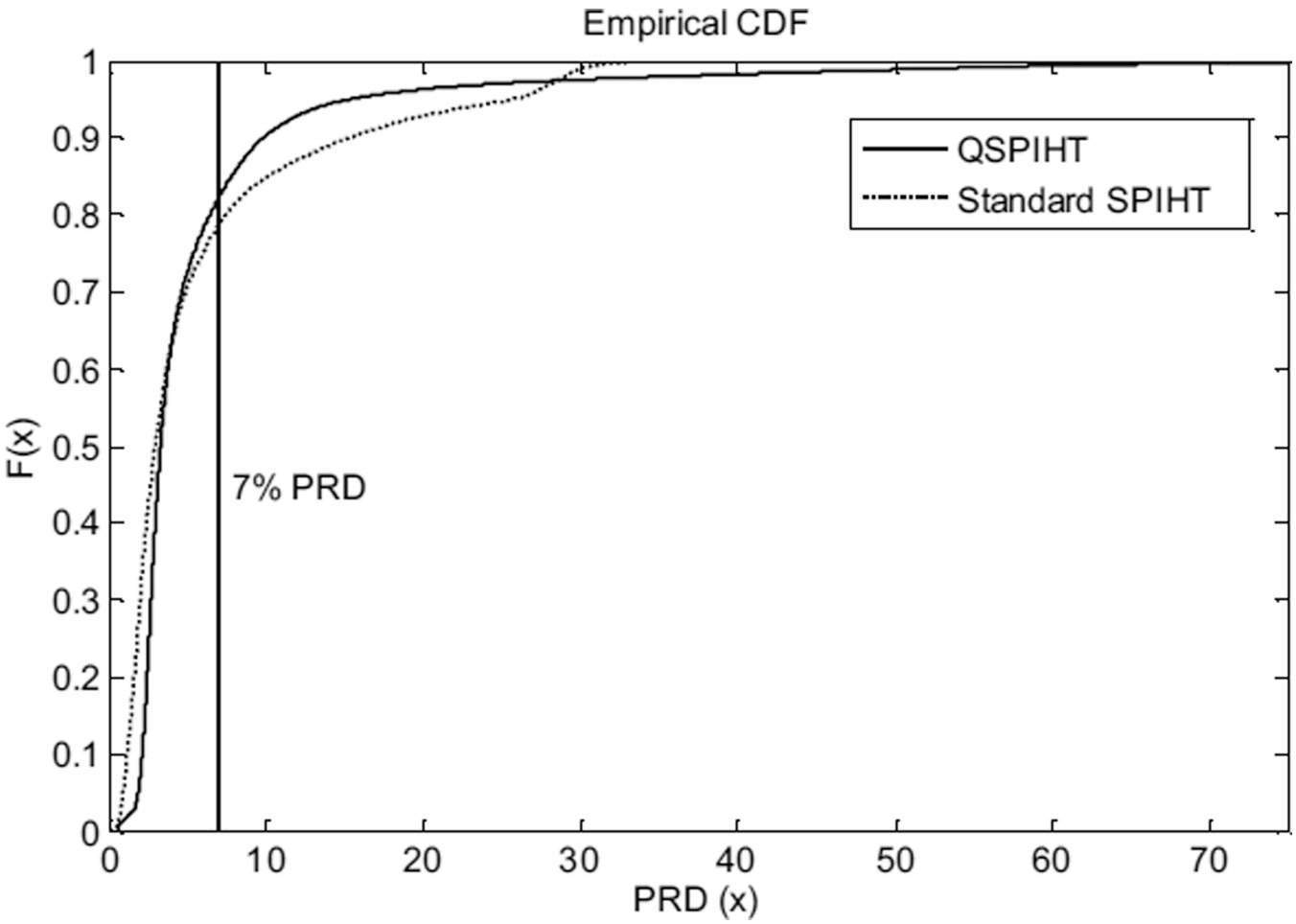

Figure 3.
Cumulative Distribution Function of PRD Results per Frame at proposed 7% PRD Settings

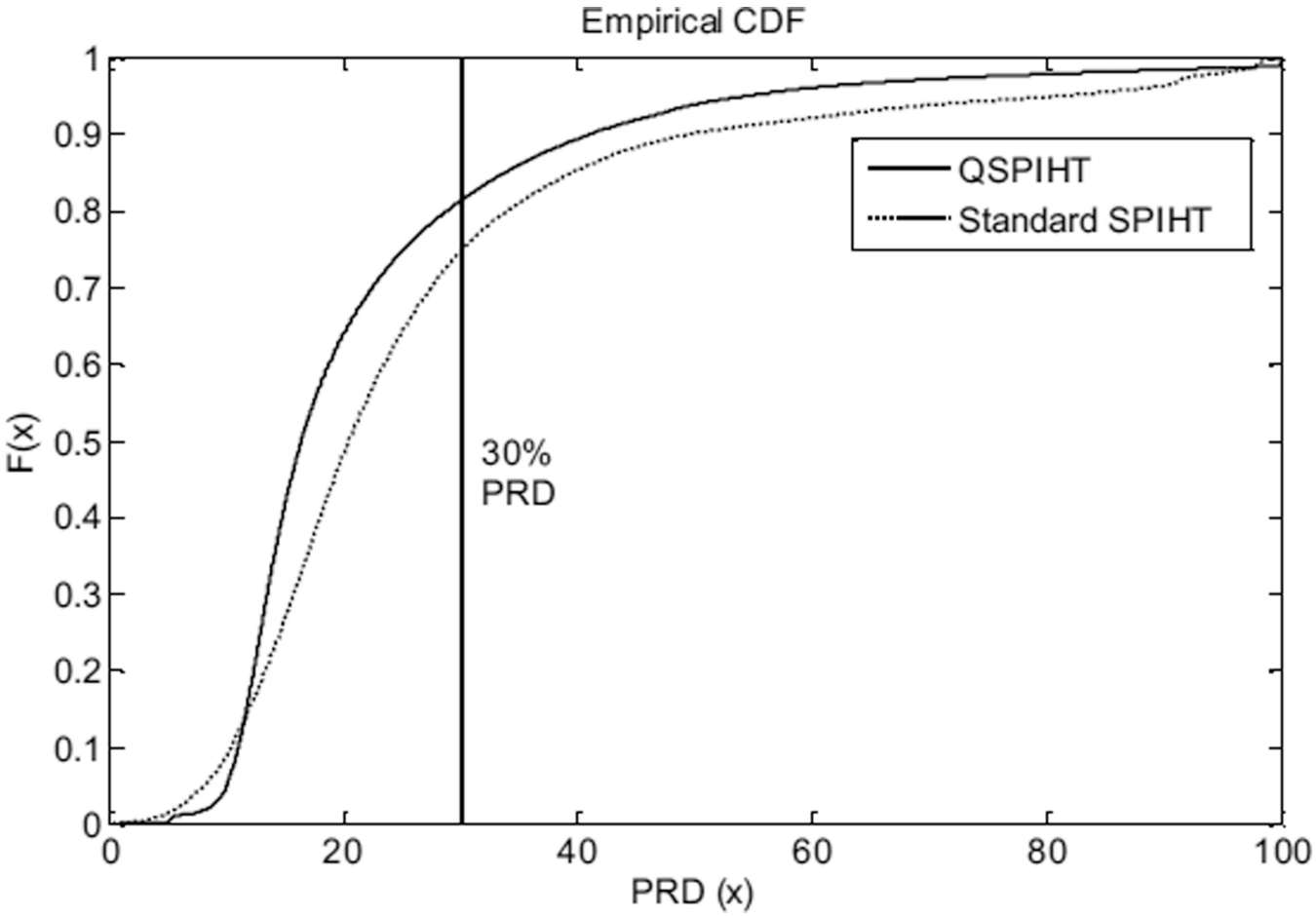

Figure 4.
Cumulative Distribution Function of PRD Results per Frame at proposed 30% PRD Settings

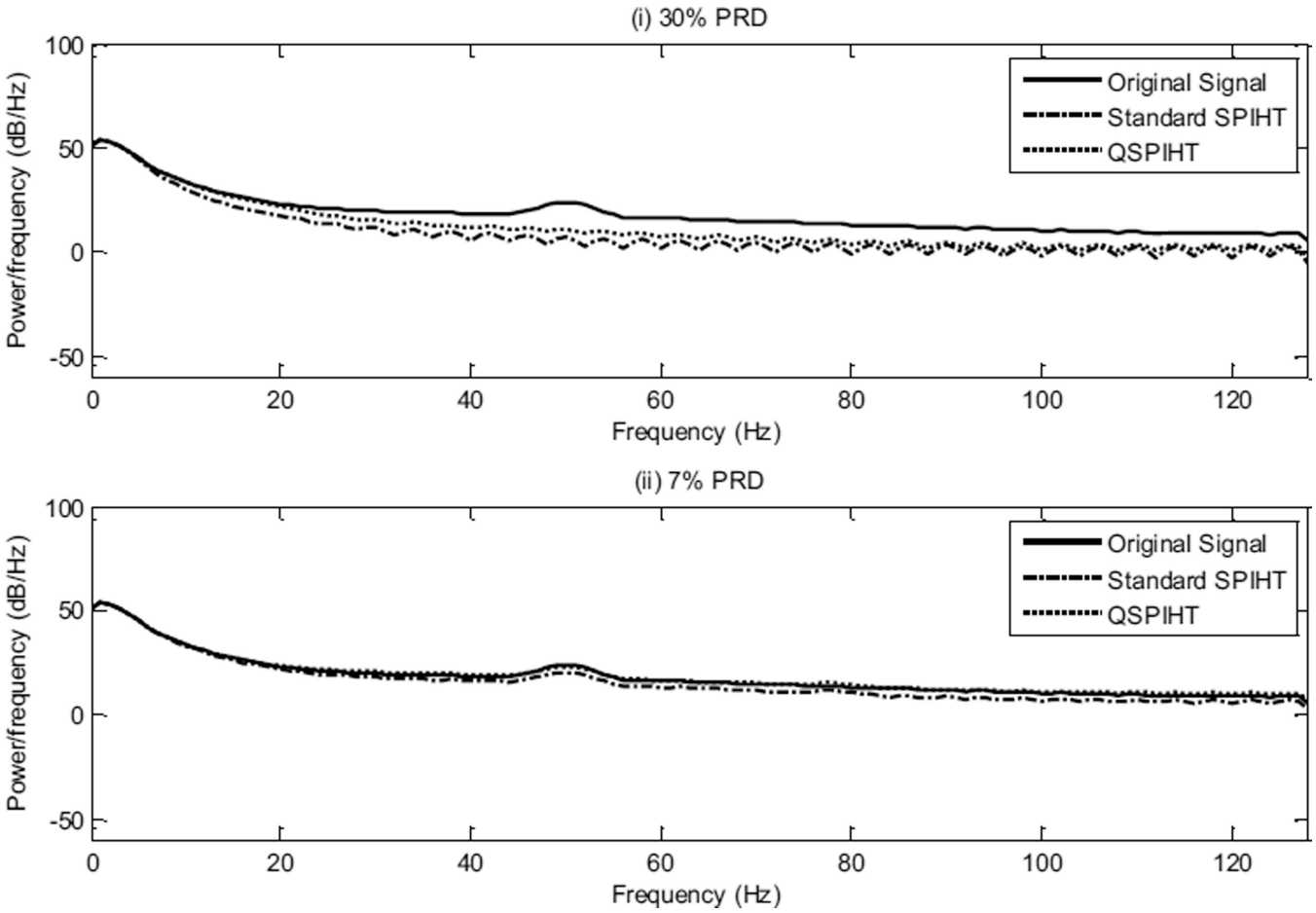

Figure 5.
Welch Power Spectral Density (PSD) of non-seizure EEG sample

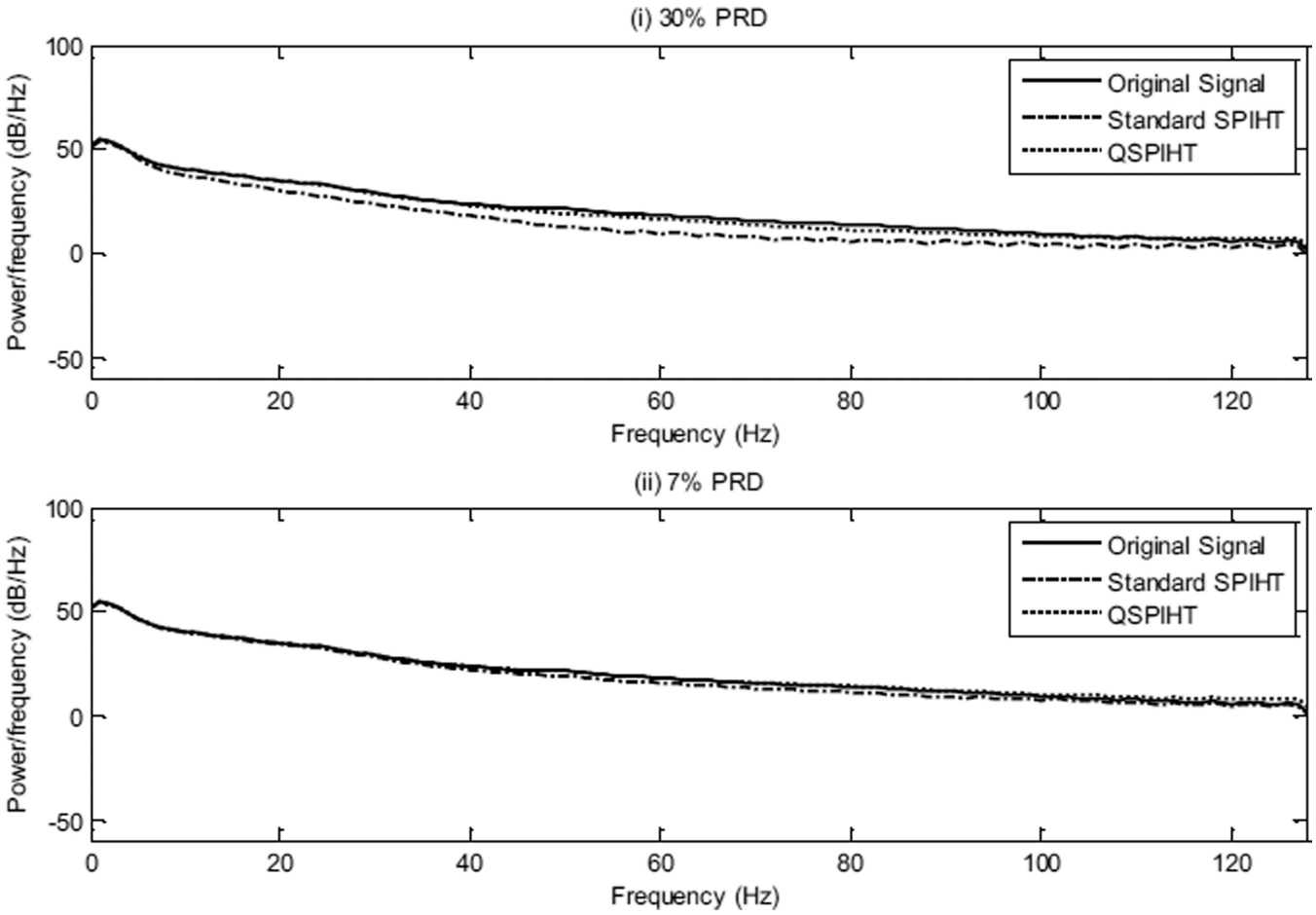

Figure 6.
Welch Power Spectral Density (PSD) of EEG sample containing seizure

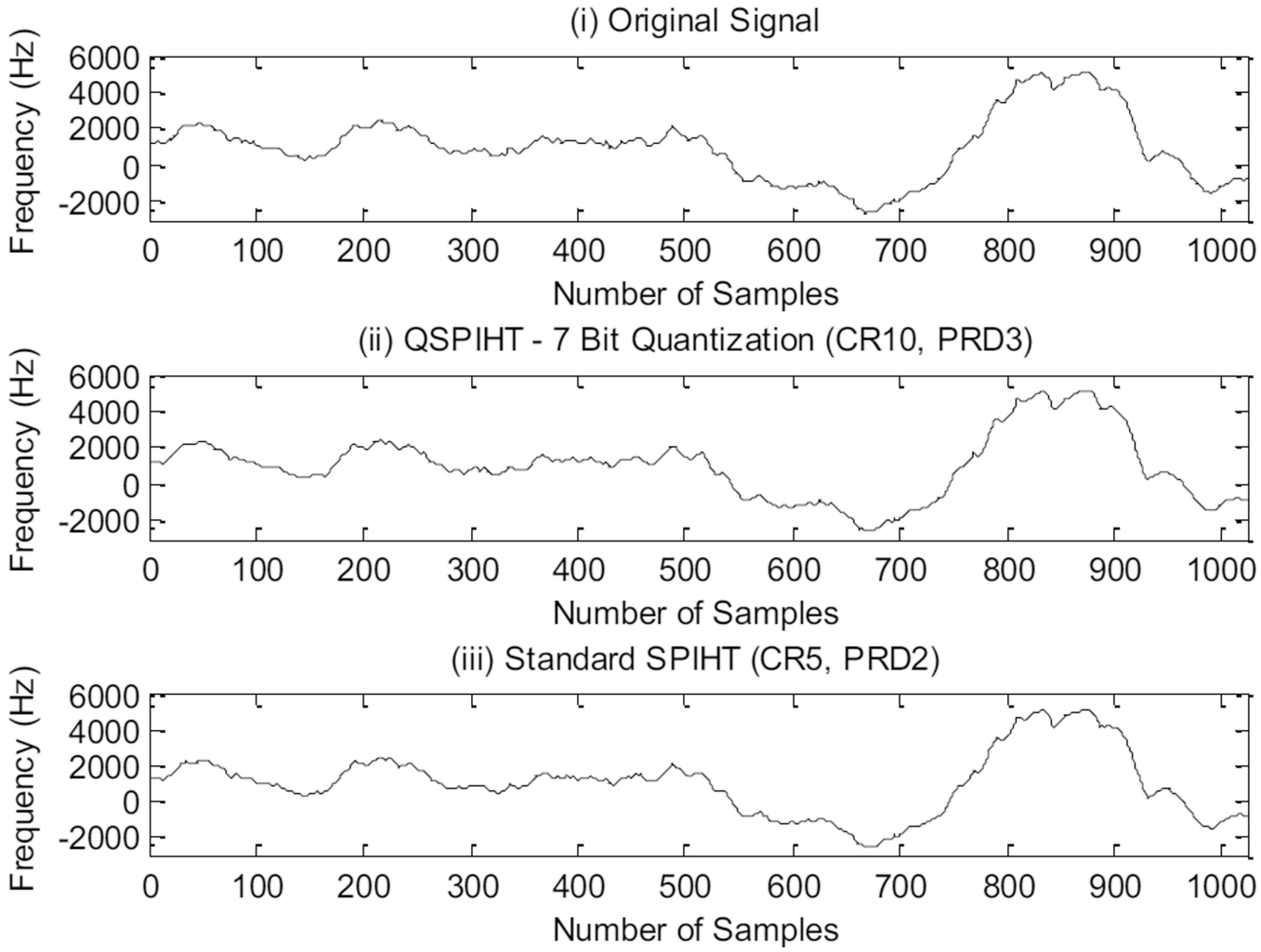

Figure 7.
Plot of sample EEG signal. (i) Original EEG Signal, (ii) Signal compressed with QSPIHT at Q7 and (iii) Standard SPIHT at CR5

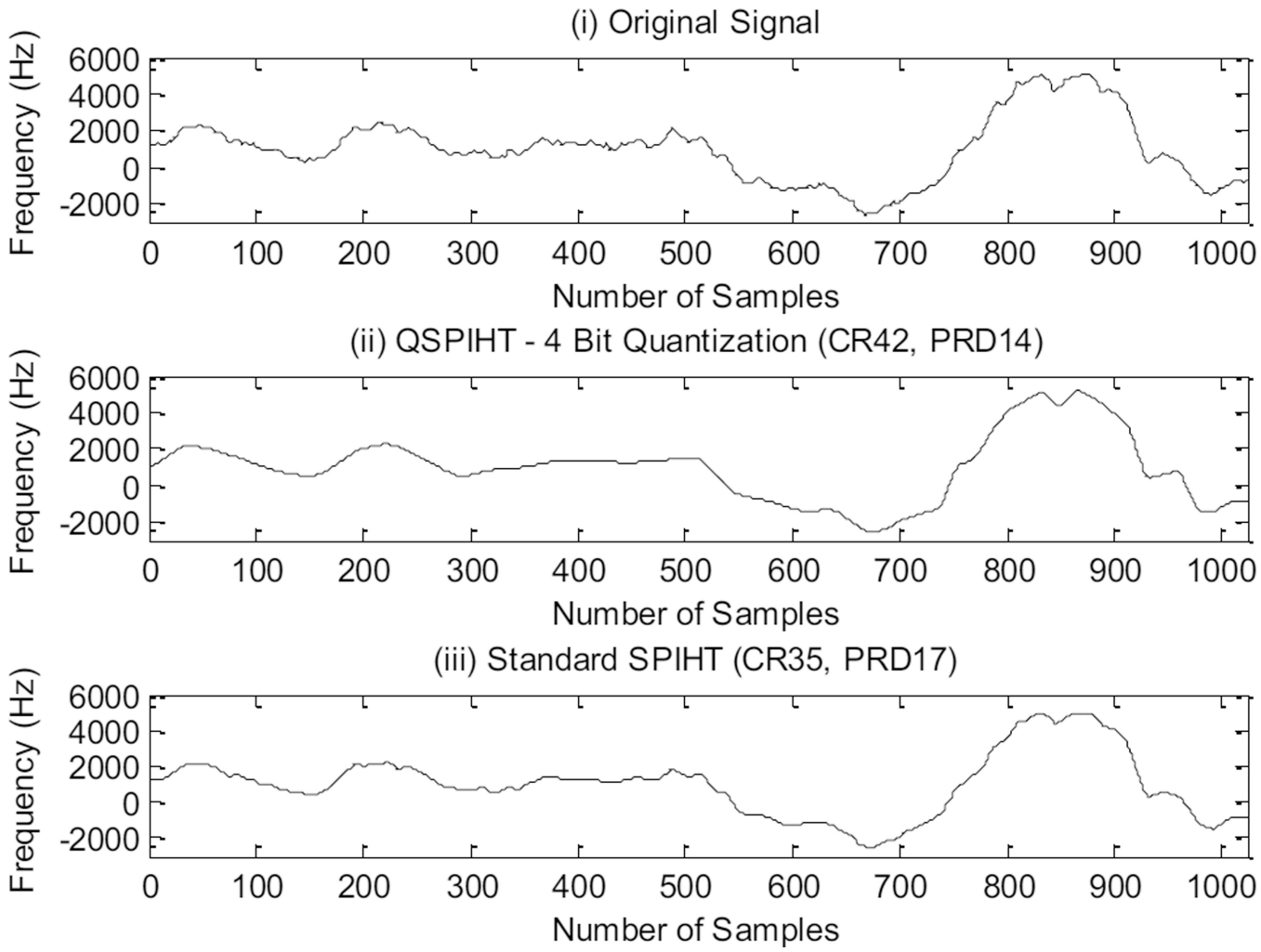

Figure 8.

Plot of sample EEG signal. (i) Original EEG Signal, (ii) Signal compressed with QSPIHT at Q4 and (iii) Standard SPIHT at CR35

Table 1

Results for Standard SPIHT Compression

Expected CR	Actual CR	Average PRD (%)	Standard Deviation (%)
200	202.36	63.49	20.67
160	160.75	58.63	20.29
110	110.87	50.78	19.73
55	55.38	36.97	19.08
40	40.29	31.40	18.92
35	35.24	29.26	18.85
30	30.24	26.90	18.50
10	10.25	12.29	11.02
7	7.26	8.94	8.97
6	6.26	7.67	7.95
5	5.26	5.99	6.18
2	2.28	0.52	0.34

Table 2

Results for QSPIHT Compression

Bit Level	QSPIHT CR	Average PRD (%)	Standard Deviation(%)
1	613.20	68.15	13.18
2	260.13	50.09	15.43
3	128.78	35.04	15.23
4	70.88	23.66	13.88
5	40.14	15.58	12.11
6	22.39	9.89	9.56
7	13.05	6.09	7.00
8	8.14	3.67	5.09
9	5.51	2.18	3.66
10	4.11	1.32	2.89
11	3.27	0.83	2.49
12	2.74	0.56	2.34
13	2.36	0.42	2.29
14	2.09	0.34	2.28
15	1.88	0.31	2.27

Table 3

CR and PRD results for QSPIHT run on MIT-BIH Polysomnographic and CHB-MIT Scalp EEG databases [27]

	MIT-BIH Polysomnographic		CHB-MIT Scalp EEG	
Bit Level	**CR**	**PRD(%)**	**CR**	**PRD(%)**
4	34.4721	29.8875	24.3321	16.5954
5	20.0354	19.2435	13.4155	10.0279
6	13.021	11.8092	8.0243	5.7098
7	9.5024	6.9341	5.3314	3.0815
8	7.3393	4.0791	3.9292	1.6105
9	3.7265	2.5436	3.1403	0.8410