# Lossy Compression Techniques for EEG Signals

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***Abstract*— Electroencephalogram (EEG) signal has been widely used to analyze brain activities so as to diagnose certain brain-related diseases. They are usually recorded for a fairly long interval with adequate resolution, which requires considerable amount of memory space for storage and transmission. Compression techniques are necessary to reduce the signal size. As compared to lossless compression techniques, lossy compression techniques would provide much higher compression ratio (CR) by taking advantage of the limitation of human perception. However, that is achieved at the cost of introducing more compression distortion, which reduces the fidelity of EEG signals. How to select a suitable lossy EEG compression technique? This motivates us to survey those existing lossy compression algorithms reported in the last two decades. We attempt to analyze the algorithms and provide a qualitative comparison among them.**

***Keywords*— *electroencephalogram signal, data compression, compression ratio, percentage root-mean-square difference***

## I. Introduction

Recent advance in electronic circuits, computer science and software engineering has made it possible for us to achieve digitization, storage, synthesis and transmission of all kinds of analogue signals, which include biosignals such as electroencephalogram (EEG), electrocardiogram (ECG) and electromyogram (EMG) for the health inspection of brain, heart and muscles, respectively. In particular, EEG signal emerges as an efficient signal that can be utilized to predict brain diseases, epilepsy and sleep distortion. With a modern wearable device, EEG signal could be uninterruptedly recorded up to 14 days [1], which has promoted the widespread use of EEG applications such as Ambulance EEG monitoring (AEEG), telemedicine, brain-computer interface (BCI) [2-8], and provided patients a cost-effective way to monitor their health in real-time.

EEG signals are usually used to record brain wave based on 10-20 international system with electrodes placed at 10, 20, 20, 20, 20 and 10% of the total nasion-inion/left-right preauricular distance. For some special applications, it is able to extend this 10-20 system by placing electrodes in between thus resulting in 32, 64, 128 and even 256 channels. Long term (up to several months) recording of EEG signal are required especially in the diagnosis of epilepsy [9], which unfortunately produces a huge amount of data. This problem has been seen as one of the major challenges in EEG data storage and processing. As such, EEG compression has been widely studied.

EEG compression can be classified into two categories, namely lossless and lossy compression. Lossless compression ensures that the data size is reduced without any loss of information, which produces a compressed file with larger size in bytes as compared to lossy compression. The performance of compression techniques are usually measured in terms of compression ratio (CR) and percentage root-mean-square difference (PRD). CR for lossless compression ranges from 1.48 to 6.63, with PRD up to 9.21 as reported in [10-12], which is far less than the CR (up to 30) achieved by lossy compression [13]. However, how much loss is acceptable? This question remains unaddressed for decades. For example, Set Partitioning in Hierarchical Trees (SPIHT) algorithm could achieve CR from 2:1 to 140:1, while the corresponding average PRDs were found to vary from approximately 3% to 50% [14]. Furthermore, after compression, does the reconstructed signal preserve the clinical information for diagnostic purpose? Cardenas-Barrera, J. et al. [15] stated that for the most popular clinical applications, distortion less than 10% is acceptable. Motivated by these two important questions, we attempt to revisit those lossy compress techniques reported in the last two decades that achieve $PRD \leq 10\%$ , and compare their performance in terms of CR.

The rest of this paper is organized as follows. Section II presents the background information related to EEG compression. Section III reviews the current approaches in lossy compression of EEG, followed by a brief summary in Section IV. Section V concludes the paper.

## II. EEG and EEG Lossy Compression

### *A. EEG*

Unlike periodical signals such as ECG, EEG does not feature a distinguished waveform. Frequency spectrum of a typical EEG signal is from 1Hz to 100 Hz with the amplitude from about 10μV to 100μV, which is classified to six bands: delta (0 – 4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), gamma (30-100Hz) and Mu (8-13Hz, partially overlapped with other bands). Fig 1 show the first 4 seconds of typical normal EEG signal sample taken from chb01_27, PhysioBank. The clinical recorded signal not only represents the neurological status, but also interlaces with the mental condition of the subjects. As the main role of EEG is to examine abnormalities in human brains, there are unpredictable abnormal transients such as epileptic strikes and focal non-epileptic form abnormal mixed with the normal signals. Fig 2 shows the transition of EEG from seizure stage to normal stage. Because of the inherited randomness and low amplitude of EEG signals, it is challenging for one to find an efficient compression algorithm.

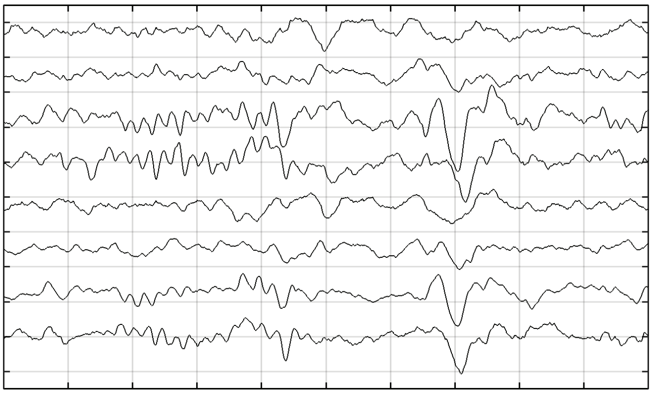

Fig 1. Typical EEG signal [16]

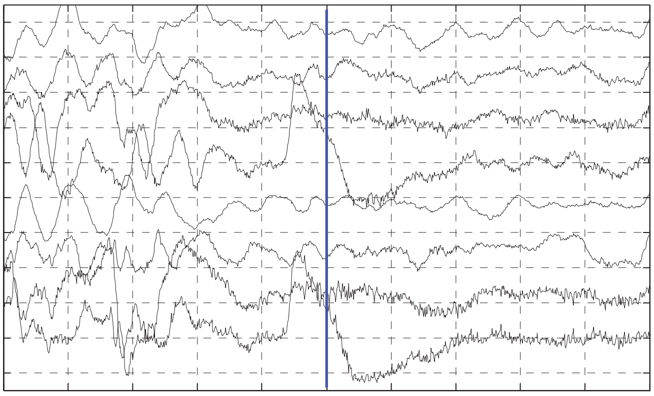

Fig 2. EEG signal with seizure [16]

### *B. Lossy Compression*

Lossy compression was first introduced in the late 1980s to compress multimedia data such as audio, video and still images by taking advantage of the limitation of human eyes. Similarly, in EEG signals compression, lossy compression attempts to remove the redundancy among signal segments and different channels.

The typical lossy compression algorithm have three layers: transformation, quantization and encoding. Transformation algorithm such as Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete Wavelet transform (DWT) are used to change the pixels in the original signal into frequency domain coefficients. To compress the signal, only those significant coefficients are selected and the remaining are discarded according to specific criteria. The selected coefficients are considered for further quantization and entropy encoding. Quantization itself is the concept of lossy compression by compressing a range of value to discrete value. Popular quantization include DCT, DWT and vector quantization. The last step can be carried out by predictive coding, arithmetic encoder or SPIHT.

### *C. EEG Database*

As shown in Table II, most researches on EEG compression were based on online available database, which enforces research consistence by making it possible for others in biomedical research community to verify the proposed method. The vastly used EEG signals are from the database of PhysioBank [16-18] and the database published by University of Freiburg, Freiburg, Germany [19].

PhysioBank provide free access to a large amount of EEG signals include Polysomonographic data BHI-MIT, Scalp Database CHB-MIT. The first database is a collection of recordings of multiple physiologic signals during sleep. Subjects were monitored in Boston's Beth Israel Hospital Sleep Laboratory for evaluation of chronic obstructive sleep apnea syndrome. Signals was sampled at 200Hz with a resolution of 12 bits per sample for four-, five- and six-channel. The second database was collected at the Children's Hospital Boston from 22 pediatric subjects with intractable seizures. Data was collected at a sampling frequency of 256Hz, with a resolution 16 bits per sample, and using up to 23 channels for several days.

Database from University of Freiburg includes the EEG signals were collected from 21 patients suffering from medically intractable focal epilepsy. EEG signals were continuously recorded up to 24 hours, using 128 channels with a sampling frequency at 256 Hz and a resolution of 16 bits per sample during an invasive pre-surgical epilepsy monitoring. However, this database is available for purchase only.

The other studies based on specific demand under the research ethics commitment included database recorded at EEG lab of Montreal Neurological Institute – Canada, the database from cMEA lab of National Tsing Hua University and database from Alain Delorme.

TABLE I. EEG SIGNAL DATABASE

| *Database* | *Notation* |
|---|---|
| BHI-MIT | DB1 |
| CHB-MIT | DB2 |
| University of Freiburg | DB3 |
| Montreal Neurological Institute | DB4 |
| National Tsing Hua University | DB5 |
| Alain Delorme | DB6 |

### *D. Performance Metrics*

The performance of compression algorithm is measured by CR and PRD. CR is defined as the ratio of the size original data to that of the compressed data.

$$CR = L_o / L_c \tag{1}$$

where $L_o$ and $L_c$ denotes the EEG signal size in bytes before compression and after compression, respectively. Lossy compression achieved CR from 2 up to over 600 with PRD approximate 70%. Ref. [14] stated that SPIHT exhibits a clear advantage, achieving CR of 120 without affecting seizure detection. PRD is the standard measure to determine the distortion between two signals [1]:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}\left(x[n]-x'[n]\right)^2}{\sum_{n=1}^{N}\left(x[n]\right)^2}} \times 100\% \qquad (2)$$

where $x[n]$ represents the original EEG signal; $x'[n]$ represents the compressed signal and $N$ represents the numbers of samples. In common applications, it is acceptable that PRD is less than 10% [15]. Higgins et al [13, 20] applied the reconstructed EEG signals to REACT, state-of-the-art seizure detection algorithm [21] and found that the seizure detection rate in terms of receiver operating characteristic (ROC) area curve could reach 90% with PRD up to 47%.

## III. Analysis of Lossy EEG Compression

Current EEG compression approaches can be classified into four groups: (i) wavelet-based, (ii) filter-based, (iii) predictor and (iv) other non-wavelet compression.

### *A. Wavelet Compression*

The most popular compression technique based on wavelet transform reported a CR about 5 to 6 [13, 20, 22-24]. Most of these works exploited the inherent similarities among EEG channels using SPIHT [13, 22, 24-26]. Higgins et al. adopted CDF 9/7 wavelet as a transform method and applied SPIHT coding in [13] and arithmetic coding in [20, 23] to achieve the same CR and PRD. Daou and her co-authors [22] reported that the same result could be achieved by using 5 levels of biorthogonal 4.4 discrete wavelet transform (DWT) before SPIHT. By preforming 1-D DWT before SPIHT, one could remove the redundancy between different sub-bands efficiently and obtain higher CR (up to 6) [24]. The authors claimed that their technique could be applied in portable biomedical devices because its low computation cost can largely reduce system power consumption.

Applying the same technique of biorthogonal 4.4 DWT before SPIHT, Daou added dynamic reference list to compute and send the de-correlated sub-bands coefficients [27]. It could not only achieve higher CR (about 7) but also detect the seizure activities with an accuracy up to 90%. Higgins et al. achieved CR of 8 while maintaining the low power consumption. They used modified CDF 9/7 by adding a new step to limit the resulting wavelet coefficients and to emphasize the sparse characteristic of EEG signals [28].

H. Daou attempted to solve the inverse and forward problems of signal and reported a CR of 10.77, by examining thoroughly the intrinsic dependency inherent between EEG channels [29]. This work is convincing since it was applied on a big database of 29 channels. The author also claimed that the PRD was independent of the database.

With the effort of finding out the most promising wavelet packet, Cardenas had compared the performance of Daubechies 6 to 10, Symplets 4 to 8 and Coiflets 3 to 5 and concluded that Daubechies 8 wavelet packet, 5 levels of decomposition and 7-bit quantization scheme provided the best result of CR up to 9.06 while maintaining PRD as low as 5.32% [15]. Their work had been assessed by medical experts to prove that the reconstruction signal preserve the clinical information with fairly good acceptance. Moreover, the proposed wavelet packet can be applied in real time with a low computation cost.

Higgins et al. compared the performance of lossy SPIHT and the method of changing the quantization level of the discrete wavelet transform coefficient before making use of SPIHT as an lossless entropy encoder (QSPIHT) [26]. For conventional SPIHT, they fixed the quantization resolution at 16 bits per sample and set CR from 2 to 200 before decompressing. The CR of 6 was reported at a PRD of 7%. With QSPIHT, the EEG signals was compressed at range of 1 to 15 bit of quantization before encoding using lossless mode of SPIHT. The achieved CR was 13.05 at a PRD of 7%.

### *B. Filter-Band Based*

Instead of transforming using wavelet package, Carlo applied Cosine modulated filter-band to split EEG signal into clinical significant sub-band before coding by the method of retained energy [30]. Their approach allowed that the quality of reconstructed signals were controllable by applying an efficient computing method to determine the threshold value in the decomposition domain. CR of 11.23 were reported for multichannel compression and 18.18 for single channel compression.

Bazan-Prieto et al. showed that using Nearly-Perfect Reconstruction Cosine-Modulated filter-band to split EEG signal into clinical significant sub-band before quantizing and coding could help achieve higher CR(12.62) while preserving clinical information in high quality [31].

### *C. Neural Network Predictors*

A quality-on-demand compression scheme with a neural network predictors and arithmetic encoder was proposed by varying the threshold of error level and quantization levels. N. Sriraam carefully examined three neural network model of single-layer perceptron, multi-layer perceptron and Elman network and obtained CR up to 5.21 with PRD less than 5% [32]. It was proved from the experimental results that single-layer perceptron preserved the high quality clinical information.

### *D. Clustering Analysis*

Hakan et al. proposed a new method based on classified signature and envelope vector sets to examine the similarity of EEG signal segments, then cluster using k-mean clustering algorithm [33]. They achieved a CR of 10.1 at a PRD of 7.15%. The authors also compared their proposed method with the wavelet transform by applying Daubechies 4, Coiflet 2, Biorthogonal 4.4, CDF 9/7 and claimed that the proposed method outperformed other methods.

### *E. Matching Pursuit*

To utilize the “best matching” projection of EEG signal onto Gabor over-complete dictionary, Yanling combined the matching pursuit algorithm and genetic algorithm to accomplish the sparse decomposition fast and efficiently [34]. Their technique resulted in a forceful CR of 18 with low PRD of 2.15%. The computation cost of the fitness function were shown to be increased 5 times as compared with the conventional method in time-frequency domain.

## IV. DISCUSSION

Compression of EEG signals encourages the research and development of emerging medical applications such as telemedicine and AEEG system to enhance health care system and human life quality. The lossy compression features a promising technique for EEG signal based on its benefit in high CR especially in some special application in field of automatic detection of disease such as seizure and epilepsy [7, 35-37]. It was shown that SPIHT displays a clear advantage, achieving CR of 120 without impact on seizure detection [14].

Table II shows a summary of current approaches. Most of them were based on wavelet compression and achieved CR up to 10 with tolerated distortion level. The others took advantages of analysis the sparse characteristics of EEG signal in order to obtain higher CR up to 18. We found that the characteristics of database play an important role in the performance of compression techniques. Applying the same technique may lead to different CRs even in an EEG signal from different channels or patients in the same database. Higher CR were reported with the signals from people with disease such as seizure and epilepsy as compared to those from healthy people.

Most works were based on wavelet transform and coded by SPIHT. This is because wavelet based compression analyzes the whole matrix to preserve high quality of restored signals while the state-of-art SPIHT is best match with wavelet transform to exploit the inherent similarity among the signal segment in single channel EEG as well as among different channels.

It was proved that the seizure detection can achieve an accuracy up to 95% with PRD from 0 to 60% in the conscientious research for seizure detection by REACT while applying the reconstruction EEG signal after compressed by comparing the detected seizure with the annotation seizure signal in the Freiburg database [20]. Daou studied the effectiveness of three specific lossy compression algorithms (Dipole based, dictionary based and 2D SPIHT) on seizure detection by TP which is represented for the period of one minute or more of overlap occurs between a seizure section in the compressed file and a seizure section in the original file and claimed that a maximum value of TP of 100% was achievable [36]. The other works [7, 14, 27] also mentioned the possibility of applying lossy compressed for EEG signal, especially in seizure detection.

Besides compression efficiency, power consumption is another key factor under consideration for real time applications. An energy consumption of 20.89nJ was reported when applying algorithm of Gaowei in SMIC 65nm CMOS [24]. Taking the advantages of the development of semiconducting materials, author in [8] successfully built the EEG sensor package with size of $40x25mm^2$, weight less than 100g. In addition, authors in [5, 7, 28, 35] proved the feasibility of applying their compressed techniques in wireless EEG monitoring systems and AEEG.

## V. CONCLUSION

This paper surveys the lossy EEG compression techniques published in the last two decades by evaluating the CR at specific range of signal distortion in terms of PRD. We found it is promising to apply lossy compression in real time applications such as tele-monitoring health care systems, AEEG systems and automatic seizure detection systems. It is clear that the sparse characteristics of EEG signal must be thoroughly studied in order to achieve higher CR with minimized distortion. The following aspects are worthy further studying: (i) group similar EEG segments by arranging the signal to 1D, 2D or 3D matrices; (ii) find out the signal sample then subtract the original signal by that sample to reduce the signal resolution; (iii) smoothing and (iv) determine the common atom for the dictionary off-line. These have been left out for our future work in this area.

TABLE II. SUMMARY OF EXISTING LOSSY EEG COMPRESSION TECHNIQUES

| *Ref.* | *T* | *$N_c$* | *$f_s$* | *N* | *DB* | *Disease* | *Technique* | *CR* | *PRD (%)* | *Remarks* |
|---|---|---|---|---|---|---|---|---|---|---|
| [38] | * | * | 5K | * | DB5 | * | MCoSaMP with DCT and Bernoulli matrix | 2.5 | 9.1 | |
| [20] | >100 | 6 | 256 | 16 | DB3 | epilepsy | JPEG2000 | 5 | 10 | Test the reconstructed signal with REACT. Seizure detection 90% with PRD = 30% and CR=8. |
| [13] | * | 6 | 256 | 16 | DB3 | seizure and non-seizure | CDF 9/7 biorthogonal DWT; code with SPIHT | 5 | 7 | Seizure detection 90% with CR=30 |
| [22] | 1 | 29 | 200 | * | DB4 | | Biorthogonal 4.4 DWT (5 level); code with SPIHT; pre-process by smoothing | 5 | 7 | |
| [23] | 24 | 6 | 256 | 16 | DB3 | seizure and non-seizure | JPEG2000; arithmetic code | 6<br>5 | 10<br>7 | Reach CR up to 4 with PRD = 3%. |
| [24] | 1 | 16 | 256 | 16 | DB2 | seizures | Perform 1-D DWT before NLSPIHT | 6 | 10.04 | Low computaion cost, can be applied in portable biomedical devices. |
| [26] | * | 6 | 256 | 16 | DB3 | seizure and non-seizure | Traditional SPIHT | 6 | 7 | CR of approximately 40 at PRD = 30% |
| [27] | * | 29 | 200 | 16 | DB2<br>DB4 | pediatric subjects with intractable seizures | Biorthogonal 4.4 DWT; code with SPIHT | 7 | 10 | Seizure detection 90% with CR>20 |
| [28] | 24 | 6 | 256 | 16 | DB3 | seizure and non- | CDF 9/7 DWT (modified) | 8 | 10 | |

| *Ref.* | *T* | $N_c$ | $f_s$ | *N* | *DB* | *Disease* | *Technique* | *CR* | *PRD (%)* | *Remarks* |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | seizure | | | | |
| [30] | 4 | 18 | 250 | 12 | DB1 | sleep apnea | Retained energy-based coding | 11.23 | 10.45 | |
| [15] | * | * | 250 | 12 | DB1 | sleep apnea | Wavelet Daubechie-8 | 9.06 | 5.32 | low computation cost, can be apply real time |
| [32] | * | 6<br>1<br>* | 256<br>256<br>173.61 | 16<br>16<br>12 | * | Epilepsy with sudden seizure | Neural network predictions with arithmetic encoder | 5.21 | <5 | Single-layer perceptron achieve best result |
| [33] | * | * | 173.61 | 12 | * | * | Classified signature and envelope vector sets | 10.1 | 7.15 | Examinate many EEG signals from different database |
| [29] | * | 29 | 200 | 16 | DB2<br>DB4<br>DB6 | pediatric subjects with intractable seizures | Dipole fitting | 10.77 | 10 | |
| [30] | 1 | 23 | 256 | 16 | DB2 | pediatric subjects with intractable seizures | Retained energy-based coding | 11.23 | 10.45 | Max CR = 18.18 for single channel |
| [31] | * | 2 | 250 | 12 | DB1 | sleep apnea | Nearly-Perfect Reconstruction Cosine-Modulated Filter band (N-PR CMFB) | 12.62 | 10.03 | |
| [26] | * | 6 | 256 | 16 | DB3 | seizure and non-seizure | Progressive lossy quantisation before employing SPIHT losslessly | 13.5 | 7 | CR over 100 at PRD = 30% |
| [34] | * | * | * | * | * | * | Matching pursuit | 18 | 2.15 | Do not specify the EEG signal |

Notations: $T$—time (hour), $N_C$—number of channels, $f_s$—sampling rate (Hz), $N$—resolution (bit), DB—database, *—unstated in the original reference.

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