THE EFFECTS OF LOSSY EEG COMPRESSION ON ERP ANALYSIS

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ABSTRACT

This paper analyzes lossy data compression in the specific context of event-related potential (ERP) analysis of electroencephalography (EEG) data. The lossy data compression techniques analyzed here are bit-rate quantization and frequency truncation using the discrete cosine transform (DCT). Within the context of both methods it is demonstrated that ERP analysis waveforms yield significant data compression advantages over raw EEG data. It is found from the experimental results that for any given quantization error bound, utilization of ERP analysis requires approximately 3 fewer bits per EEG sample than normalized EEG data. Additionally, given any error bound for frequency truncation, at least 30% more total DCT coefficients can be discarded when utilizing ERP analysis instead of raw EEG data. The results hold significant implications for large-scale medical applications that rely on ERP analysis of EEG data.

INTRODUCTION

Electroencephalography (EEG) is a method of recording the brain's electrical activity and is widely used as a medical diagnostic tool. Recent interest in creating publicly available databases of EEG datasets [1, 2] has led to a renewed need to consider the problem of compressing EEG waveforms to decrease storage space requirements and download times. Many of the EEG compression methodologies that have been studied to date have been lossless or near-lossless [3, 4, 5] due to clinical liability considerations. The difficulty with lossless schemes is that the maximum compression achievable is often minimal, being limited by the entropy of the input signal. While lossy compression can overcome this difficulty, careful consideration must be given to the manner in which the EEG waveforms will ultimately be utilized in order to preserve diagnostically significant data (e.g., [6]).

A particularly potent tool for understanding EEG is event-related potential (ERP) analysis, which has been shown to have widespread utility in the detection of neurological disorders [7, 8, 9, 10, 11, 12, 13], brain-control interfaces (BCI) [14, 15, 16], understanding brain processing [17, 18, 19], and even for evaluating the perceptual quality of audio stimuli [20]. ERP waveforms are created by time aligning multiple sections of raw EEG waveforms using appropriate temporal markers while performing renormalization (i.e., ‘removing the baseline’) to compensate for voltage drift [21] and then averaging the derived trials. This research considers the problem of lossy compression in the context of how it affects ERP analysis. Specifically, the paper analyzes the impact of two fundamental lossy compression techniques, namely quantization and frequency truncation, on the accuracy of an extracted ERP waveform.

ERP ANALYSIS OF QUANTIZED EEG DATA

A. *Quantization of EEG Data*

We first normalize the raw EEG waveforms by channel which allows us to simulate the process of quantization using the formula

$$x_k[n] = \Delta \cdot round[\frac{x_k[n]}{\Delta}] \tag{1}$$

with quantization step size $\Delta = 2^{-b}$, where b is the number of bits used per input sample. Due to the bipolar nature of EEG data, the true number of bits used per sample must be adjusted to $b + 1$. The dataset used in these experiments is the sample dataset included with the EEGLAB toolbox and consists of 32 channels sampled at 128 Hz for a duration of 240 seconds, resulting in 30504 frames per channel [22]. The dataset contains 80 temporal markers indicating the presentation of a stimulus to the subject. All frames for each channel are quantized using (1) for the range $b = 1$ to $b = 9$, that is, 2 bits per sample to 10 bits per sample. At each level of quantization, the mean squared error (MSE) between the normalized EEG data and the quantized dataset is calculated over individual channels as well as over the entire dataset. Of the 32 channels represented in the data set, two have especially notable significance. The F4 electrode (channel 5), located on the front right quadrant of the subject’s scalp, shows the most pronounced P300 response to stimuli of the test while the O2 electrode (channel 32), located on the back right of the subject’s scalp, demonstrates the least pronounced P300 response. The P300 is a time domain waveform that is characteristic of early-brain processing and ERP analysis will typically accentuate the P300 if it is present [21], motivating our attention toward the extremes of this response.

B. *Impact on ERP Analysis*

We then perform event-related potential analysis at each quantization level (2 bits per sample to 10 bits per sample) on the normalized EEG data. As described above, ERP analysis averages all time-aligned trials obtained from the 80 temporal markers within the normalized EEG waveforms while performing renormalization to minimize the effects of voltage drift. The MSE between the ERP analysis of the original normalized EEG data and the ERP analysis of the quantized datasets is calculated for each level of quantized data, both across the individual channels and across the conglomerate of channels.

Table 1 shows results of the error analyses for the normalized EEG data and ERP analysis at selected quantization levels and Figure 1 plots those results on a linear plot. In the plot we include the analyses of the whole data sets ('All Channels') as well as channel 5 and channel 32 individually because of the significance of their P300 responses. For all analyses, however, we observe the variation in error due to data compression between these two extreme channels to be minimal and sufficiently approximated by the whole dataset.

Table 1: Mean Squared Error for Quantized Datasets

Bits Per Sample	Normalized EEG	ERP Analysis	Ratio
2	1.8591e-02	2.5979e-04	71.560
3	5.0205e-03	6.4163e-05	78.246
4	1.2930e-03	1.6274e-05	79.455
5	3.2604e-04	4.1831e-06	77.942
6	8.1289e-05	1.0299e-06	78.925
7	2.0356e-05	2.5296e-07	80.468

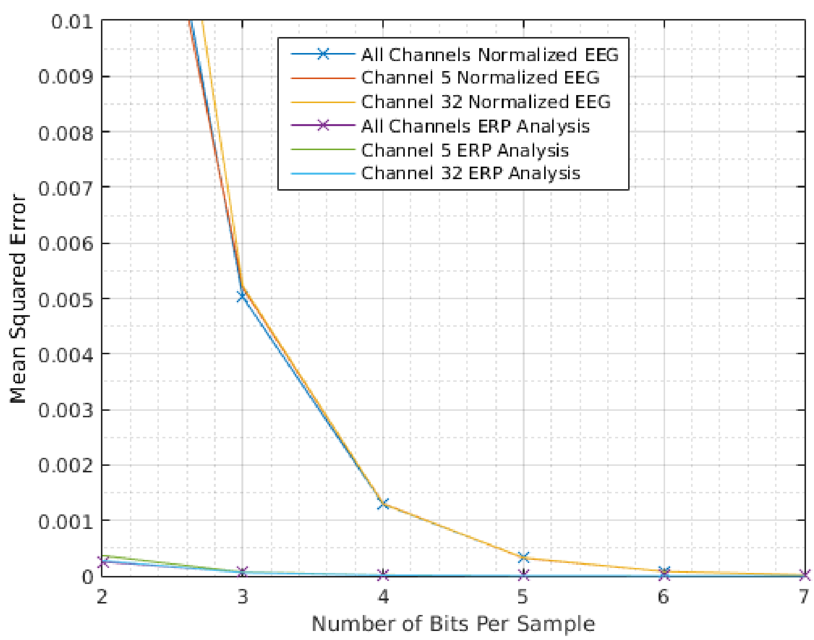

Figure 1: Quantized Normalized EEG Data and Subsequent ERP Analysis

Table 1 and Figure 1 demonstrate the drastic decrease in MSE from the normalized EEG dataset to the ERP analysis dataset for all quantization levels. The final column in Table 1 shows the ratio of the MSE of the normalized EEG dataset to the MSE of the ERP analysis at each quantization level. The MSE ratios across the range 2 bits per sample to 10 bits per sample have a standard deviation of 2.93. This statistic is substantially smaller than that for the DCT-based frequency truncation and allows relatively more uniform conclusions for bit-rate quantization regarding the relationship between the compressed EEG datasets and the associated ERP analyses.

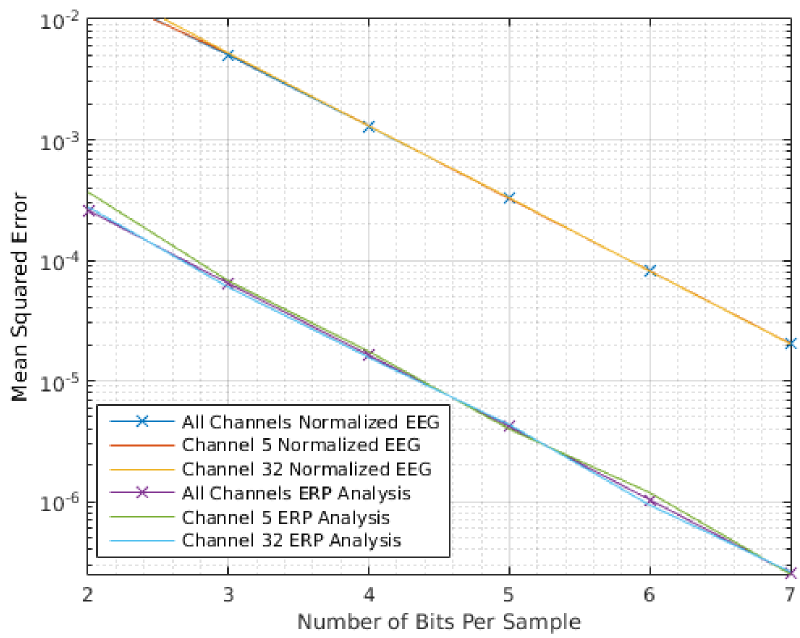

Figure 2: Quantized Normalized EEG Data and Subsequent ERP Analysis (Log-Lin Plot)

The semi-log plot in Figure 2 is helpful in drawing conclusions regarding the relationships between the normalized EEG data and the corresponding ERP analysis under quantization. Keeping the number of bits per sample fixed on the horizontal axis, we can observe the MSE ratios between the EEG data and the ERP analysis data as enumerated in Table 1. If we fix the MSE on the vertical axis, that is, identify a quantization error bound, we can interpret bit-rate relations between the normalized EEG waveforms and the ERP analysis datasets. At MSE 10^{-4}, for example, we must increase nearly 3 bits per sample across the horizontal axis from the ERP analysis data point to reach the normalized EEG waveform data point. It is clear from the plots in Figure 2 that such is the case for any quantity of MSE and therefore we find that utilization of ERP analysis requires approximately *3 fewer bits per EEG sample* than the normalized EEG data for any given quantization error bound.

Plots of the waveforms as shown in Figures 3 and 4 qualitatively support the interpretations above. Here, we show a sample waveform from the F4 electrode (channel 5) (i.e., the one with the strongest P300 response). Figure 3 illustrates the effects of quantization (at 4 bits per sample) on the normalized EEG waveform while Figure 4 illustrates the effects on the ERP waveform. We note that the quantized ERP waveform mirrors its non-quantized waveform far more closely than the quantized raw EEG waveform follows its non-quantized version.

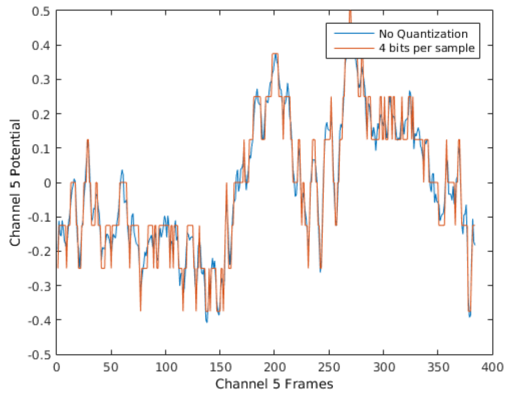

Figure 3: Visual Sample for Normalized EEG Data

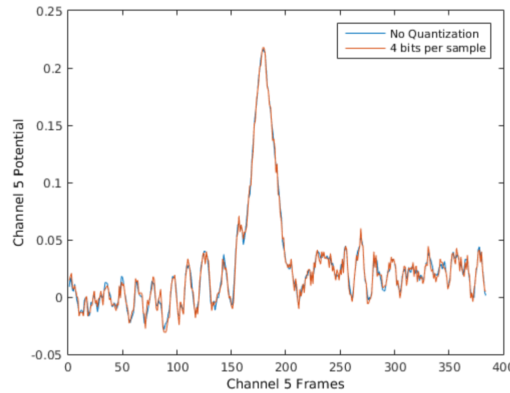

Figure 4: Visual Sample for ERP Analysis

ERP ANALYSIS OF FREQUENCY TRUNCATED EEG DATA

C. *Frequency Truncation Using the Discrete Cosine Transform (DCT)*

A second method of lossy compression we investigate is using the discrete cosine transform (DCT) to perform frequency truncations: i.e., retaining only the highest energy frequency coefficients and zeroing out the remainder. The DCT is closely related to the discrete Fourier transform but has a stronger energy compaction property, meaning that most of the signal information is described by fewer coefficients. This property of the DCT makes it favorable for signal compression. Here, each individual channel vector $x(n)$ of length N in the sample data set is put through the DCT-II transform given by

$$y(k) = \sqrt{\frac{2}{N}} \sum_{n=1}^{N} x(n) \frac{1}{\sqrt{1+\delta_{k1}}} \cos\left\{\frac{\pi}{2N}(2n-1)(k-1)\right\} \qquad k = 1, ..., N \tag{2}$$

with δ_{k1} the Kronecker delta. In order to perform various levels of frequency truncation, between 10% and 90% (using 10% intervals) of the lowest energy coefficients are zeroed out. Following the modification of the DCT coefficients, the inverse of the DCT-II transform is performed, resulting in lossy compression of the original EEG data with various percentages of frequency coefficients discarded. For each percentage of discarded coefficients, the MSE between the original EEG data and the compressed result is calculated over individual channels and as well as the entire dataset.

Table 2: Mean Squared Error for Frequency Truncated Datasets

Coefficients Discarded	EEG Waveform	ERP Analysis	Ratio
10%	1.1508e-02	1.6384e-04	70.238
30%	3.4173e-01	4.5692e-03	74.790
50%	1.9629e+00	2.5663e-02	76.486
70%	7.9978e+00	9.7699e-02	81.862
90%	4.5723e+01	4.9171e-01	92.987

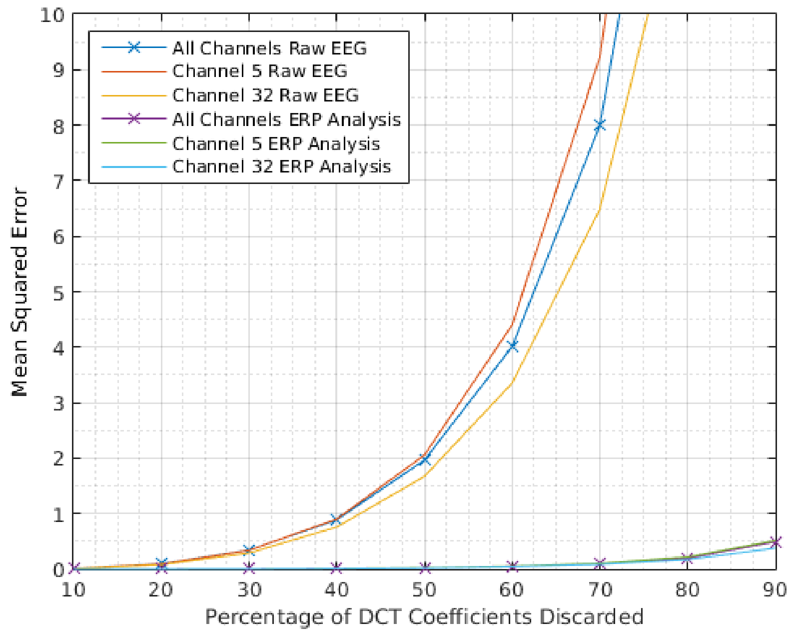

Figure 5: Frequency Truncated Raw Data and Subsequent ERP Analysis

D. Impact on ERP Analysis

Next, we perform event-related potential analysis with each percentage of the DCT-based frequency truncated EEG data. Once again we perform renormalization during ERP analysis to minimize any voltage drift within the EEG scan. We then calculate the MSE between the uncompressed ERP analysis dataset and the ERP analysis datasets resulting from each percentage of discarded low energy coefficients.

Table 2 and Figure 5 compare the frequency truncation rate against the MSE for both the EEG datasets and the synthesized ERP datasets. Although we see here slightly larger variations in MSE between the individual channels and the dataset as a whole than we did for quantization, the result for the entire dataset remains sufficient to quantify the effects of frequency truncation on ERP analysis. The final column of Table 2 shows the ratio between the MSE of the EEG waveform and the MSE after the ERP analysis at selected percentages of coefficients discarded. The MSE ratios across the range 10% to 90% of the coefficients discarded have a standard deviation of 6.94, a noticeably larger statistic than for the bit-rate quantization discussed previously. The larger variance in the MSE ratio for the DCT-based frequency truncation complicates the conclusions that can be drawn between the compressed EEG waveforms and the corresponding ERP analyses.

The semi-log plot in Figure 6, however, is helpful to identify relations between the frequency truncated EEG waveforms and the corresponding ERP analysis datasets. Fixing the percentage of DCT coefficients discarded on the horizontal axis, we can observe the MSE ratios between the EEG waveforms and the ERP analysis datasets as enumerated in Table 2. If we fix the MSE on the vertical axis, that is, identify an error bound for frequency truncation, we can draw important comparative conclusions between the ERP analysis datasets and the EEG waveforms. At MSE

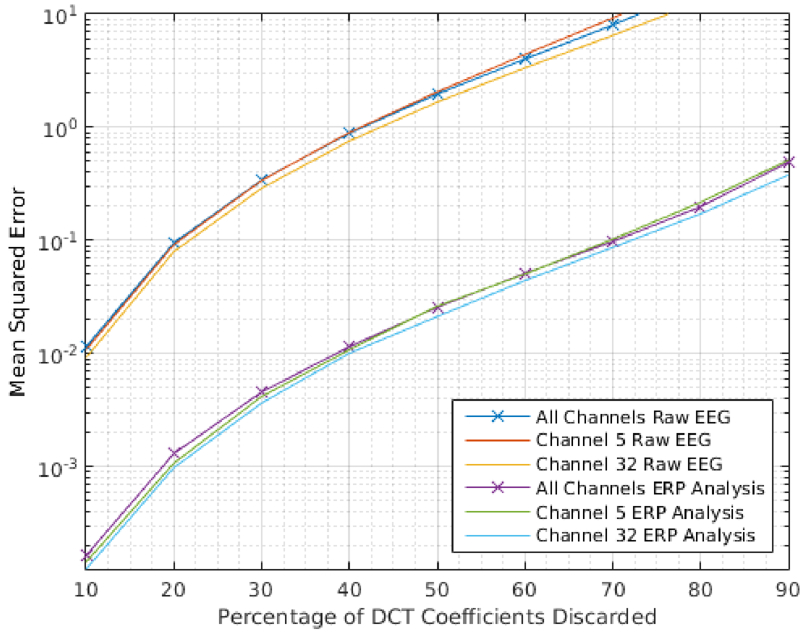

Figure 6: Frequency Truncated Raw Data and Subsequent ERP Analysis (Log-Lin Plot)

10^{-2}, Figure 6 shows that the raw EEG dataset can only discard 10% of the DCT coefficients whereas the ERP analysis dataset has discarded 40% of the DCT coefficients, meaning that an additional 30% of the total DCT coefficients can be discarded when utilizing ERP analysis rather than EEG waveforms for the selected error bound. At MSE 10^{-1}, the raw EEG dataset can only discard 20% of the DCT coefficients whereas the ERP analysis dataset has discarded 70% of the DCT coefficients, meaning that an even larger additional 50% of the total DCT coefficients can be discarded when utilizing ERP analysis rather than EEG waveforms for that selected error bound. Following the same inspection process, we note that the additional percentage of total coefficients that can be discarded when utilizing the ERP analysis steadily increases from MSE 10^{-2} to 10^{-1} and levels off for MSE greater than 10^{-1}. Therefore we find that for any error bound for frequency truncation, at least an *additional 30% of the total coefficients in the DCT* can be removed when utilizing the ERP analysis rather than the raw EEG waveforms, and that as the permitted error bound increases, we can discard as much as an extra 50% of the total coefficients in the DCT for the ERP analysis compared to the raw EEG waveforms.

This trend can be visually verified using waveforms sampled from the F4 electrode (channel 5) (strongest P300 response). Figure 7 demonstrates the effects of frequency truncation (at 80% of DCT coefficients discarded) on the raw EEG waveform while Figure 8 demonstrates the effects on the derived ERP analysis datasets. Studying these figures, we clearly see that the frequency truncated ERP waveform matches its uncompressed version far more closely than the frequency truncated raw EEG waveform matches its uncompressed version.

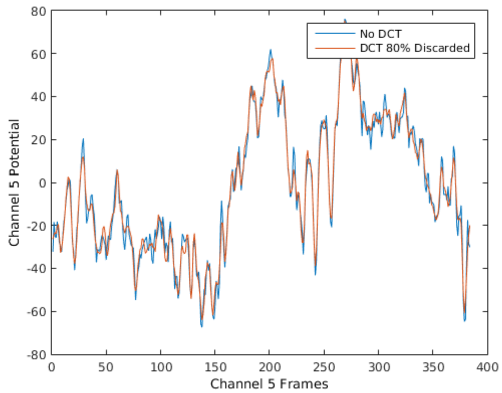

Figure 7: Visual Sample for Raw EEG Data

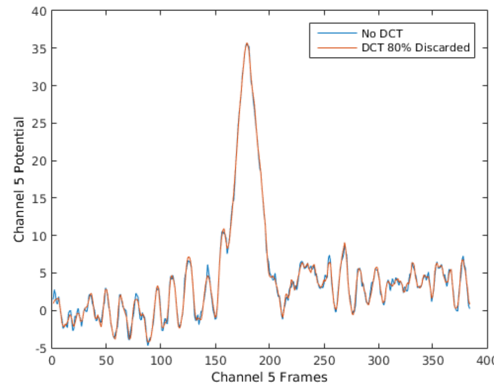

Figure 8: Visual Sample for ERP Analysis

CONCLUSIONS

In this paper, we have examined how the lossy compression techniques of quantization and frequency truncation affect EEG data destined to be processed into ERP waveforms. For both quantization and frequency truncation, it is observed that utilization of ERP analysis waveforms yields significant data compression advantages over raw EEG data. Specifically, given any quantization error bound, utilization of ERP waveforms requires approximately three fewer bits per EEG sample than normalized EEG data. Given any error bound for frequency truncation, utilizing ERP waveforms rather than raw EEG data permits at least 30% more of the total DCT coefficients to be discarded. Taken together, these results support the idea that lossy compression of EEG waveforms is a viable solution to the problem of efficiently storing and transmitting EEG signals for those applications that use ERP analysis. Future work includes examining the effects of lossy compression on other important EEG analysis techniques such as time-frequency analysis and cross-frequency coupling analysis.

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