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A two-dimensional approach for lossless EEG compression

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ABSTRACT

In this paper, we study various lossless compression techniques for electroencephalograph (EEG) signals. We discuss a computationally simple pre-processing technique, where EEG signal is arranged in the form of a matrix (2-D) before compression. We discuss a two-stage coder to compress the EEG matrix, with a lossy coding layer (SPIHT) and residual coding layer (arithmetic coding). This coder is optimally tuned to utilize the source memory and the *i.i.d.* nature of the residual. We also investigate and compare EEG compression with other schemes such as JPEG2000 image compression standard, predictive coding based *shorten*, and simple entropy coding. The compression algorithms are tested with University of Bonn database and Physiobank Motor/Mental Imagery database. 2-D based compression schemes yielded higher lossless compression compared to the standard vector-based compression, predictive and entropy coding schemes. The use of pre-processing technique resulted in 6% improvement, and the two-stage coder yielded a further improvement of 3% in compression performance.

1. Introduction

Electroencephalogram (EEG) is a record of electrical activity of the brain. EEG provides a large-scale and robust measure of the dynamic activity of brain; it has high temporal resolution but poor spatial resolution. Though, EEG is considered as a valuable source for understanding neuronal functions and neurophysiological properties of human brain. EEG is used successfully for diagnosing brain disorders (e.g., Alzheimer's disease [1]), in sleep studies, monitoring depth of anesthesia, and in cognitive studies [2].

Various clinical applications require acquisition, archiving, transmission and automatic processing of EEG over an extended duration (several days, weeks, or potentially even months). Such long-term recordings results in massive EEG data sets. For instance, accurate inverse modeling demands the use of higher number of EEG channels (e.g., 256), and higher sampling rate may be required (several kHz in the case of cortical EEG; several hundred Hz for scalp EEG), to capture spikes and high-frequency oscillations in the EEG. On the other hand, the number of patients with neurological disorders is increasing, and hence this put forward the need for efficient and flexible compression techniques.

Signal compression is achieved by exploiting correlations in the source. The compressibility of the signal is dependant on the amplitude distribution of the signal and the power spectrum of the signal. For instance, if a single value dominates the amplitude distribution, or a single frequency dominates the power spectrum, then the signal is highly compressible. The amplitude distribution and spectral distribution of a segment of EEG is shown in Fig. 1.

Usually, the amplitude of EEG signal is very low (few μV), and the acquisition systems amplify the signal more than a million times. This leads to amplification of noise as well. This inherent noise makes the compression difficult, and poses a hindrance in achieving good compression performance.

There are three types of correlations in a multi-channel EEG signal

1. Intra-channel correlation among the adjacent samples of the signal from the same channel.
2. Inter-channel correlation among the samples acquired at the same instant of time over all the channels.
3. The brain rhythms (e.g., alpha-rhythm) also introduce correlations in EEG, but they fluctuate with time.

We briefly review the EEG compression literature in the following groups: (i) predictive schemes, (ii) transform based schemes, (iii) multichannel schemes.

1.1. Predictive schemes

EEG signal is often modeled by an auto-regressive (AR) process. AR predictor predicts the current sample as a weighted sum of previous samples. To achieve perfect reconstruction, the resid-

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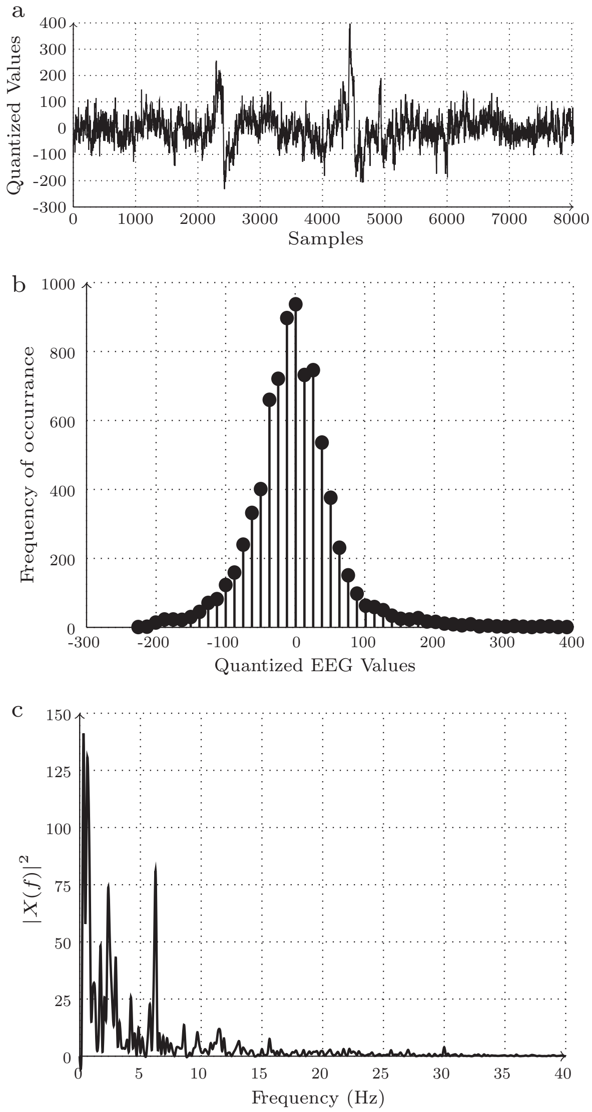

Fig. 1. Compressibility of EEG. (a) EEG signal, (b) amplitude spectra, and (c) power spectra of the signal shown in (a).

ual signal is transmitted together with the predictor coefficients. Lossless predictive schemes directly code the residuals, whereas lossy predictive schemes threshold and quantize the residuals to improve compression rate (at the cost of increased error). Various prediction models have been developed: this include linear AR model [3,4], recursive-least-squares predictor [5], adaptive neural networks [6] and models based on chaos theory [7]. Refinements such as context-based bias cancellation [4], and adaptive error modeling schemes [8,9] further improve the performance.

1.2. Transform based schemes

Consider a sequence of N signal samples X, as a N-dimensional vector. A compact representation Y in the transform domain is obtained by orthogonal transformation, $Y = TX$, where T denotes the transformation matrix. In lossy compression, M most significant components are selected such that $M \ll N$, whereas the residual signal (signal corresponding to remaining N–M transform domain coefficients) is also coded for lossless compression. The key idea is to exploit the properties of the transform domain elements (Y) such as sparsity, regularity, to form a compact code. Transforms applied include discrete cosine transform [3], sub-band transformation [10], wavelet-packet transform [11], and integer lifting wavelet transform [12,13].

1.3. Multichannel compression schemes

Predictive and transform based compression schemes operate naively on EEG signals without using any domain-specific knowledge. EEG signals recorded from spatially adjacent channels possess a high degree of correlation, which can be used to design efficient compression techniques. Techniques proposed to compress multi-channel EEG include graph-theoretic based approach [14], Karhunen–Loeve transform [15], exogenous input model [16] and vector quantization [3].

Apart from the above-mentioned EEG compression schemes, some ad hoc methods also have been designed for EEG compression: genetic algorithm based fractal EEG coding [17], EEG approximation by extracting patterns (classified signature and envelope set) [18]. The emerging field of compressed sensing opens the way to acquire signals with very few random measurements (compression while sensing), well below the Nyquist rate. For acquiring signals with compressed sensing, the signals need to be sparse in some domain (e.g., time–frequency domain). Some studies used compressed sensing and finite rate of innovation techniques to compress EEG [19,20].

Lossless compression techniques compress the signal by removing redundancies, while allowing perfect reconstruction of the original signal waveform. In lossless predictive coding, the residuals are also coded along with the predictive coefficients. In lossless transform coding, integer transforms are selected to ensure perfect reconstruction. Antoniol and Tonella [3] presented an excellent survey of lossless EEG compression techniques such as predictive coding, transform coding and vector quantization schemes. Lossless compression schemes often registers low compression performance compared to lossy compression, because of the inherent noise in the signal. This noise have no or very less correlation that could be exploited by the compression algorithms; in lossy compression this noise is removed to improve performance, but lossless compression schemes attempts to model this residual noise. Many schemes attempt to improve the lossless compression performance by modeling the residuals; this includes context-based bias cancellation [4] and detailed prediction residual modeling [8].

Here, we propose to utilize any inherent correlations in EEG to improve the lossless compression performance, by arranging the EEG in matrix form. In our previous work [21], we studied the Rate–Distortion (R–D) performance of two variants of an EEG compression algorithm; first one operates on the EEG arranged in the standard vector form (1-D), whereas the second variant arranges EEG in matrix form (2-D) before compression. The 2-D based compression algorithm gave substantial reduction in the distortion at low bit rates compared to the 1-D scheme. In addition, 2-D based scheme also improved the lossless compression as well. In this paper, we systematically explore the following: how to arrange EEG signal in matrix, the amount of smoothness of this matrix in time domain and transform domain (wavelet transform), and compression of this matrix with a two-stage compression scheme. We also compress EEG using JPEG2000, well-known image compression standard, lossless predictive coding (*shorten*) and entropy coding. We will show that the 2-D based schemes achieve higher performance compared to the other above-mentioned schemes.

The paper is structured as follows: In Section 2, we explain the arrangement of EEG signal in matrix form, and we analyze its smoothness in time and wavelet transform domain. In Section 3, we explain the two-stage compression scheme and the optimal lossy layer bit rate selection; we also present a brief outline of the other lossless compression schemes here. We discuss the experimental