Electroencephalographic Signal Compression Based on Adaptive Segmentation and Video Encoders

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***Abstract*— Traditionally, biological signals are generated as one-dimensional arrays (even if acquired with many channels) and consequently encoded through one-dimensional techniques. Nonetheless, some researchers have addressed the encoding of biological records as two-dimensional arrays, in such a way that signal dependencies are exploited by two-dimensional encoders (*e.g.*, video and image encoders), which are preceded by adaptation steps. The main goal of the latter is to reshape input signals and make their structures more suitable to target encoders, in order to favor dependency exploration and then provide higher performance. The present work employs a similar approach for electroencephalograms, but with the use of a new preprocessing technique, named as percentage difference segmentation, which is combined with the H.264 and high efficiency video coding compressors. Simulation results show that the proposed methodology is effective and outperforms state-of-the-art schemes present in the literature, in terms of $PRD \times$ compression ratio.**

***Keywords*— Electroencephalogram, preprocessing, data compression, high efficiency video coding, H.264.**

I. Introduction

The electroencephalogram (EEG) is a record of the human brain's electrical activity and is obtained from voltage fluctuations (electrical fields) acquired with electrodes (generally, noninvasive), which are the net result of excitatory and inhibitory synaptic potentials occurring in pyramidal neurons [1]. It can be used for patient monitoring/management, condition assessment, and it can even assist in the diagnosis of neurological and psychiatric disorders, such as Alzheimer [2], dementia [3], epileptic seizure [4], bipolar depression, and schizophrenia [5].

In addition to use of EEG signals for pathology monitoring and analysis, this signal can also be employed in control interfaces and robotics. For instance, people who are unable to use their arms or legs to perform movement could employ an array of electrodes placed across the scalp, where a system would interpret the resulting signals and control prostheses or a motorized wheelchair, facilitating user locomotion [6].

Regarding their clinical applications, EEG signals are usually acquired with multiple derivations and quantized with $16/12$ bits, at a frequency of $256/250$ Hz. In addition, when an EEG exam is used for monitoring epileptic patients, it is necessary to record many hours of brain activity [1]. Therefore, this kind of signal usually produces large datasets, which increase the need for storage and/or transmission capabilities, and consequently encourages research efforts for efficient compression schemes. Tha feature is even more important when dealing with portable or embedded systems, given the limited amount of resources. Besides providing a compact representation for input records, it is worth noticing that such methods should also be able to preserve clinical [7] and even movement direction information [8], which are contained in original signals, in order to allow their further use in advanced applications.

Biological signals (*e.g.*, electromyograms, electrocardiograms, and EEGs) can be acquired with many derivations/channels, but they essentially one-dimensional; consequently, they are stored and processed with one-dimensional methods. For instance, Khodayari-Rostamabad *et al.* [5] analyzed various EEG records, with the goal of extracting signal features (*e.g.*, spectral coherence and mutual information, among others), based on 30s overlapping epochs, and Prieto *et al.* [9] used cosine modulated filter banks, in order to directly decompose non-overlapping consecutive EEG time epochs into a set of subbands, well adapted to their characteristic frequency bands. In those cases, both consider the behavior of one-dimensional EEG signals and process them in their original form.

Recently, some researchers have used a different approach for the biological signal encoding problem, by considering the related records as images [10], [11], [12]. As a result, one-dimensional arrays are rearranged into two-dimensional matrices and then fed to image/video compressors, which are in charge of exploiting intra and intersegment redundancies. Besides, in order to increase arrangement correlation and consequently encoder performance, preprocessing techniques are usually employed [11]. Indeed, their main goal is to format input signals and make them similar to natural images, in such a way that image-compression tools are fully exploited.

The present paper devises a similar approach for the lossy compression of EEG records and proposes a new automatic segmentation procedure for creating their image representations: the percentage difference segmentation (PDS), which aims to split input signals into proportionally similar segments, with the potential to create homogeneous data regions. In

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addition, two video compressors are employed: the new high efficiency video coding (HEVC) [13] and H.264 [14].

The rest of this paper is divided as follows. In Section II, the adaptive segmentation algorithm is described, while section III tackles the proposed coding system. Sections IV and V describe the signals and evaluation metric used in the present experiments, respectively. Section VI, in turn, presents the performed simulations and discusses the results. Finally, section VII details the associated conclusions.

II. The adaptive segmentation procedure

As already mentioned, EEG signals are commonly one-dimensional. Indeed, they can even be acquired through several channels [11], [1]; however, each one represents the variation of some potentials or units, on a given skull region, over time. This way, in order to encode such signals as two-dimensional matrices, some kind of reshaping rule must be established, which is usually done by splitting biological records into segments and placing each one in the rows (or columns) of a matrix, as shown in Fig. 1. Nonetheless, as segment lengths usually influence the resulting inter and intrasegment dependencies, this kind of procedure may compromise the exploitation of signal correlations. In summary, the main goal would be to keep similar signal samples near each other, in such a way that redundancies in that area are more effectively exploited.

Some biological signals, such as electrocardiograms, may present known structures that serve as references (QRS complex) [7]; however, as electroencephalograms present a more stochastic behavior, most methods in the literature just fix the segment length or the arrangement dimensions and use preprocessing techniques, usually segment reordering ones, for improving data correlation [10], [15]. As a consequence, they have the drawback of transmitting side information, due to the new data arrangement, because decoders need to recover the associated original structures.

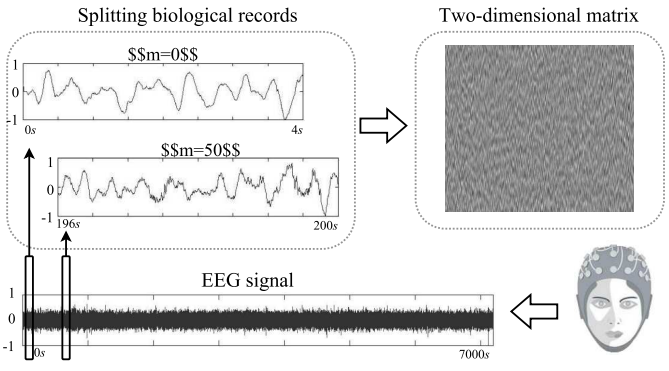

Fig. 1. An EEG signal rearranged into a two-dimensional matrix.

Therefore, one can say that the adaptation block is clearly composed by two steps: data partitioning and segment rearrangement. Besides, it is worth noticing that the latter is necessary, due to the loss of correlation between adjacent segments, which is caused by the former, because it does not usually take into account similarity or correlation measures.

As a consequence, if the developed segmentation procedure is adaptively performed, the need for data rearrangement may be significantly reduced. Indeed, the proposed segmentation algorithm aims to find the best segment length, in order to improve intra and intersegment correlations. This technique is called percentage difference segmentation, whose goal is to split the input signal based on the proportional similarity among its adjacent resulting sample segments, that is, their percentage difference (*PD*). For each pair of segments, the *PD* is computed as

$$PD = \frac{\sum_{n=0}^{N-1} (v[n] - v_{ad}[n])^2}{\sum_{n=0}^{N-1} v^2[n]}, \quad (1)$$

where v is the current segment, v_{ad} is the adjacent one, and N is the segment length. After computing the percentage difference values for all adjacent segments, for a given N, their mean value is taken and stored. Then, the chosen length is the one that presents the smallest average *PD*. The considered segment lengths are $N = 16n$, with $n = \{2, 3, \ldots, 64\}$. Indeed, such a rule is closely related to image blocks used in H.264 and HEVC and aim to improve the performance of available image compression tools.

This way, as the partitioning is carried out in order to maximize global correlation, a subsequent reordering step may not be necessary, mainly because the gain achieved with an already correlated-enhanced assembly does not normally compensate the cost of the side information.

III. The proposed compression framework

The proposed methodology is composed by three steps: signal splitting, segment rearrangement, and encoding, according to the block diagram shown in Fig. 2. First, the input EEG record is split into segments with the same length, according to the PDS procedure. Next, the resulting segments are rearranged throughout the rows of a matrix: if the last segment is incomplete, its last sample is used as padding value. Finally, the new two-dimensional formatted data is then fed to a two-dimensional encoder, which generates the compressed bit stream. Given that the resulting segments are not reordered, there is no need to transmit side information, except for the signal length (maximum of 32 bits), which is embedded in the encoded-bitstream's file header. At the decoder, all presented steps are simply executed in reverse order.

It is worth noticing that the signal splitting and also the segment rearrangement blocks are independent on the final encoder and can be developed separately. Indeed, they can be embedded into image encoders or even provided as a separated module, which only uses platform encoding infrastructures. As a consequence, that has the potential to leverage decoders that are already integrated into target platforms and result in faster implementation and adoption.

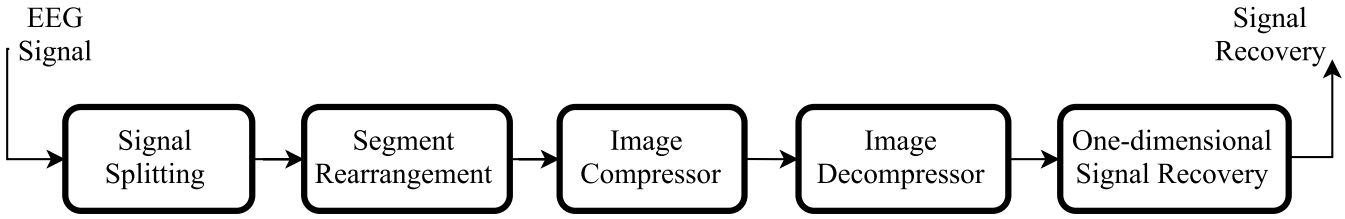

Fig. 2. The block diagram of the proposed methodology.

IV. Test signals

The performance of the proposed scheme was evaluated by running tests with EEG records from the CHB-MIT Scalp EEG database [16], which was collected at the Children's Hospital Boston. It was acquired from 22 pediatric subjects with intractable seizures and contains signals with 23 derivations (channels), which were sampled at a rate of 256 samples/s and with 16-bit/sample. The related patients were monitored for several days, with the goal of completely characterize seizures and decide for a possible surgical treatment. One should note that the use of an open access database, like the CHB-MIT Scalp EEG, is an interesting approach, because it opens the possibility of comparison with previous and future works, in a reliable manner.

In order to directly compare the results of the present work with the state-of-the-art ones provided by Prieto *et al.* [9], mean values for the same dataset created by the latter, which is composed by records selected from the CHB-MIT database and also for the F4-C4 derivation alone (for every patient in the dataset), of the same records, were taken. The mentioned dataset was designed with two records from each of the five chosen patients, amounting to 230 signals, whose details are given in Table I. As one can notice, such records were captured from subjects of different sex, with and without ictal attack, and with variable recording time, which provides as much signal variability as possible.

TABLE I
Selected dataset description

Patient	Sex	Recording time (s)	Ictal	Record
chb01	F	3600	no	chb01_02
		3600	yes	chb01_15
chb04	M	14400	no	chb04_02
		14400	yes	chb04_08
chb07	F	14400	no	chb07_02
		14400	yes	chb07_12
chb10	M	7200	no	chb10_02
		7200	yes	chb10_12
chb23	F	7486	yes	chb23_06
		14400	no	chb23_10

V. Performance measures

In order to evaluate the proposed compressor's performance, when dealing with biological signals, the percent root-mean-square difference (PRD) is widely adopted. The PRD is defined as

$$PRD = 100 \times \sqrt{\frac{\sum_{i=0}^{N-1}(x[i]-\widehat{x}[i])^2}{\sum_{i=0}^{N-1}(x^2[i]-\mu)}}, \quad (2)$$

where $x[i]$ is the original signal, $\widehat{x}[i]$ is the reconstructed one, μ is the baseline value of the analog-to-digital conversion used for data acquisition, and N is the number of samples. The variable μ is used only if the signal presents a DC level; otherwise, it is considered zero.

As the reconstructed signal quality varies with the size of the resulting compressed representation, PRD alone is not normally enough. It is then complemented with the compression ratio (CR), which is defined as

$$CR = \frac{N_{bo}}{N_{bc}}, \quad (3)$$

where N_{bo} is the number of bits in the original signal and N_{bc} is the number of bits in the compressed one.

PRD assess the reconstruction error, in terms of a percentage of signal energy, and is presented as a function of CR. This metric is useful for testing relative performance of different encoders; however, as each compression algorithm changes the target signal in its own way, a subsequent specialist analysis is always advised, in order to check if the diagnosis and movement information were preserved.

A. Simulation environment

The proposed framework was achieved by implementing the adaptation step, which is composed by signal splitting (the PDS procedure) and segment rearrangement, in C language. That module was then integrated into HEVC and H.264 reference encoders, running on Linux.

The intra prediction modes of the mentioned video encoders were used: the reference software modules for the HEVC test model 9.1 (HM) [13] and the H.264 joint model (JM) [14]. The HEVC encoder was used with rate-distortion optimized quantization (RDOQ) and deblocking filter enabled. In addition, as HEVC HM 9.1 presently only supports 4:2:0 sampled input data, a simple padding is done for converting from the 4:0:0 to the 4:2:0 format. The H.264/AVC JM used the FREext High 100 profile (that provides YUV 4:0:0 chroma

sampling format), with samples represented with 14 bits. Rate-distortion (RD) optimization, deblocking filter and context-adaptive binary arithmetic coding were enabled, as well as 8×8 blocks for both the transform and the prediction steps.

VI. Results and discussion

The proposed scheme was evaluated by running tests with the EEG signals discussed in Section IV, in order to plot $PRD \times CR$ curves. Figs. 3, 4, and 5 show the average results for each patient in the adopted dataset, regarding H.264 and HEVC encoders, and the overall average results for both, respectively. Fig. 5 also presents results for the state-of-the-art method developed by Prieto *et al.* [9]. As one can notice, the proposed scheme, with PDS allied to the HEVC encoder (PDS + HEVC), provided the best results. It is also easy to notice, from Figs. 3 and 4, that the slopes of the resulting curves do not tend to increase with higher CRs, which shows that the proposed framework is capable of encoding EEG signals with different features (seizure and nonseizure), in a consistent way. Regarding F4-C4 channels, shown in Table II, PDS allied to HEVC also outperformed Prieto *et al.* for the majority of the records, but chb10_12.

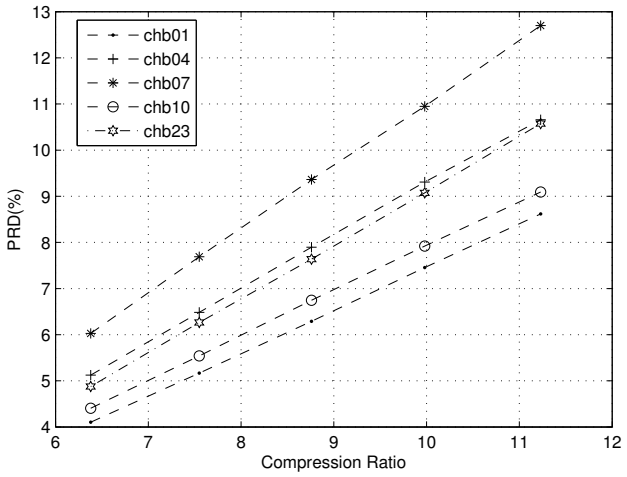

Fig. 3. Average results for each patient in the dataset created by Prieto *et al.* [9], with H.264.

Results for the H.264 encoder were not so successful in average, as can be seen from Fig. 5 and Table II, but still outperformed Prieto and HEVC for some F4-C4 channels and may be regarded as competitive. The superiority of HEVC was already expected, as its intra prediction mode is more advanced, containing 35 spatial prediction modes (H.264 contains only 9) and block sizes varying from 4×4 to 64×64 (H.264 ranges from 4×4 to 16×16, with some restrictions) [17]. Indeed, HEVC is a more advanced and flexible encoding algorithm and has the potential to adapt to data with a more specific behavior.

Differently from the proposed approach, which employs the intra prediction mode of video encoders and is consequently based on integer transforms [17], [18], the method presented

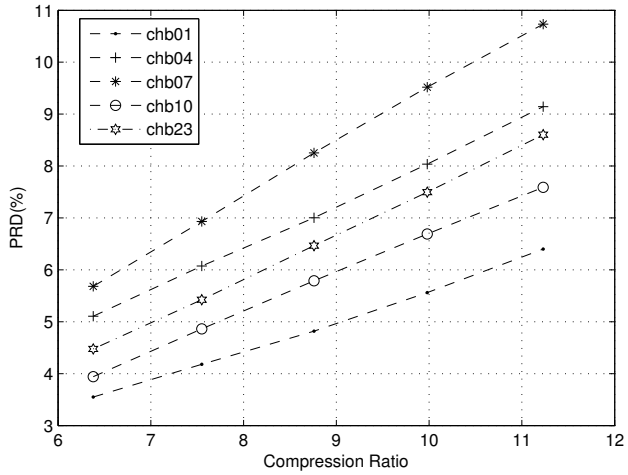

Fig. 4. Average results for each patient in the dataset created by Prieto *et al.* [9], with HEVC.

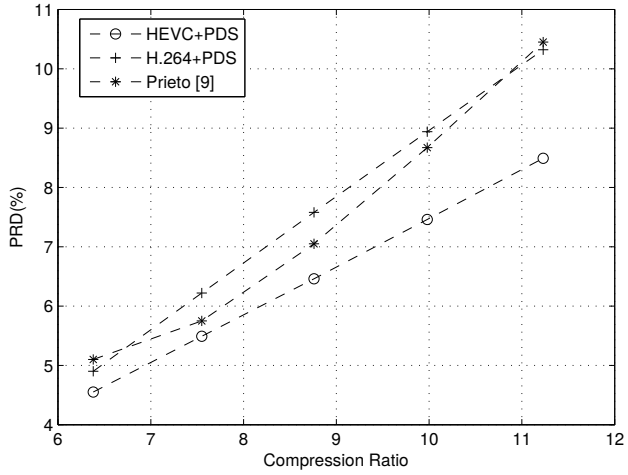

Fig. 5. Average results for the whole dataset created by Prieto *et al.* [9].

by Prieto *et al.* makes use of modulated filter banks, for decomposing the EEG signal into a set of subbands, and a thresholding-based method, for quantizing samples.

Another interesting method was proposed by Higgins *et al.* [19], which employs the set partitioning in hierarchical trees (SPIHT) algorithm. Although the EEG database used by Higgins *et al.* is no more available [20], a fair comparison is still possible, given that they used a mixture of seizure and nonseizure data, like the dataset processed by the proposed method [9]. In that case, for a PRD of 7%, which is considered the allowed loss for clinical evaluation of reconstructed EEG signals [19], a CR of 5 is achievable. Comparing with the proposed methodology, it can be seen, from Fig. 5, that the same PRD can be obtained with a CR higher than 9.0, when the HEVC variation is used.

One important consequence of the results presented here is that the development a new encoding algorithm for EEG signals one can avoided, since it is possible to adapt existing

TABLE II

$PRD(\%)$ FOR THE F4-C4 CHANNEL OF THE CHOSEN EEG RECORDS.

	Prieto *et al.* [9]		HEVC+PDS (Proposed)		H.264+PDS (Proposed)	
Signal	CR	PRD (%)	CR	PRD (%)	CR	PRD (%)
chb01_02	8.78	6.01	9.19	**5.76**	9.19	7.74
chb01_15	17.11	5.41	17.57	**4.97**	16.89	8.10
chb04_02	6.43	6.72	6.84	5.48	6.80	**5.35**
chb04_08	6.59	6.61	6.82	**4.20**	6.80	4.49
chb07_02	4.67	6.89	4.51	3.69	4.72	**3.69**
chb07_12	7.80	6.47	8.05	**6.29**	8.20	7.58
chb10_02	15.30	5.50	15.35	**5.21**	15.10	7.76
chb10_12	18.19	**5.45**	17.98	5.44	17.72	8.68
chb23_06	6.65	6.20	6.68	**5.12**	6.43	5.39
chb23_10	5.99	6.17	6.20	**3.71**	6.23	4.22

video coders and still create high-performance compression frameworks, given that a suitable preprocessing step (signal segmentation together with segment rearrangement) is performed. Besides, as the video encoders tested here are widely available in a variety of devices (even mobile ones) and also as portable software modules, the deployment of such a framework is facilitated, since it would be necessary only to develop the adaptation module and interface it with existing encoders. As a result, these advantages might trigger wide adoption of the proposed framework, both by the medical community and patients, and even speed-up its implementation.

VII. CONCLUSIONS

A new segmentation procedure was presented, which is named as the percentage difference segmentation and can be directly employed on the compression of electroencephalographic records with two-dimensional encoders. It was incorporated into existing off-the-shelf video compressors, leading to an enhancement in the quality of reconstructed signals. In the simulations carried out for validating the proposed methodology, the obtained results outperformed state-of-the-art compression methods present in the literature, with a maximum PRD of 7% at a CR higher than 9.0, when the HEVC encoder is employed, which is suitable for EEG clinical evaluation. Given the use of commercial video encoders and the good performance, it constitutes an interesting and viable solution for electroencephalogram compression, which can be even embedded into consumer electronics devices. Besides, the results shown here also indicate that it is worthwhile to pursuit techniques that adapt EEG signals to existing compressors, because such approaches have the potential to provide improvements in compression performance and reduce deployment costs of EEG compression schemes.

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