35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Compression-Ratio-Based Seizure Detection

Chung-Lin Sha, Taehoon Kim, N. Sertac Artan, and H. Jonathan Chao*

Abstract

For wireless seizure monitoring devices seizure detection and data compression are two critical tasks that need to be carefully designed against a very tight power budget to maximize the battery life. These two tasks are usually considered separately and algorithms for each are developed separately. In this paper, we consider having a single low-power algorithm for implementing both seizure detection and data compression. Towards that end, we investigated compression ratio (CR) as a seizure marker and show that the seizure detection can be achieved as a by-product of compression with no additional cost, and thus overall system power can be reduced. We show that the proposed method, the CR-based seizure detection has promising performance with 88% seizure detection accuracy, and 5.5 false positives per hour (FPh) without any computation overhead.

1. INTRODUCTION

As the data output of electrode arrays increases with new technologies [1] leading to higher number of channels and higher sampling rates, the requirements to process, transmit, and store this data increases exponentially. Therefore, the need for efficient compression have become more critical and various compression methods for neurological signals have been proposed [2–4].

For instance, data can be transmitted in compressed form for wireless seizure monitoring devices for patients with epilepsy to save transmit power. Furthermore, such devices with online seizure detection capabilities can add seizure markers to the transmitted data automatically or can be used to apply stimulation or raise an alarm when there is a seizure. However, high accuracy seizure detection algorithms [5, 6] tend to also consume high power. Since, the compression is readily running on these devices, it may be beneficial if the compression algorithm can also provide a seizure marker eliminating the need for additional processing for seizure detection. Targeting to identify such a marker, we made these two observations, which led to the identification of compression ratio as a potential seizure marker.

Firstly, the time and frequency domain signal characteristics of seizure episodes can be significantly different from normal activity. For instance, a seizure episode may follow through three phases such that the episode starts with a low-amplitude and high-frequency period and progresses into a high amplitude and low frequency period followed by a significant decrease in the signal amplitude [7]. Another way to interpret this seizure characteristic is to consider the change in the signal amplitude in these phases, where the difference between sequential samples will be small at the seizure onset, high during the seizure, and small again at the end of the episode. Secondly, if conventional compression methods such as JPEG entropy coding [8] is used to compress the EEG data, the CR will vary depending on the variability in the signal. Accordingly, it is expected that the CR will differ among the above three phases, and also with respect to the general non-seizure data. Thus, CR can potentially be used as a seizure marker and since it is readily available as a byproduct of compression, using CR as a seizure marker incurs no additional computational cost beyond the computational cost of compression.

In this paper, we present and evaluate the seizure detection potential of CR, while emphasizing that the seizure detection using compression methods incur no additional computation costs. The rest of the paper is organized as follows. Section 2 introduces the proposed method. In Section 3, compression and seizure detection performance and the power estimation for real-time processing are given. Section 4 provides a brief discussion on the results, and Section 5 concludes the paper.

2. CR-based Seizure Detection

In this section, we introduce the CR-based seizure detection, which combines the compression of the EEG

*C.-L. Sha, T. Kim (e-mail: tkim03@students.poly.edu), N. S. Artan, and H. J. Chao are with the Department of Electrical and Computer Engineering at the Polytechnic Institute of New York University, Brooklyn, NY 11201 USA.

data with seizure detection in a single operation. The proposed CR-based seizure detection consists of four blocks as shown Fig. 1.

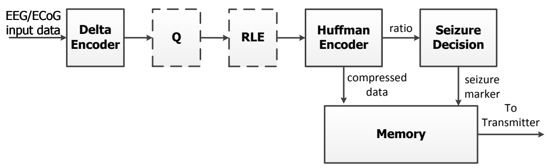

Figure 1: Block diagram for the proposed CR-based seizure detection.

The proposed method operates on every 1 sec. window of EEG data to compress the data, while determining whether this window includes a seizure. The operation of the method is as follows. First, the data window passes through the delta encoder block to eliminate temporal redundancy. For lossy compression, the output of the delta encoder is quantized (Q block) and passes through the run-length encoder (RLE) and Huffman encoder. For lossless compression, the quantization and the RLE (shown as dotted lines in the figure) are eliminated. These blocks are used for conventional entropy coding in the JPEG encoder [8].

The content of the given data window is compressed and stored in the memory after the Huffman encoder. Additionally, the CR of the Huffman encoder is calculated and used for seizure detection. The CR is calculated as follows:

$$CR = \frac{\text{compressed data size}}{\text{original data size}} \tag{1}$$

To decide whether there is a seizure in the current data window, the CR corresponding to the data window (i.e., the CR for the current 1 second data) is compared against the average of the previous 60 sec CRs. A difference between the current CR (short-term window) and the average of the previous CR (long-term window) greater than a predefined threshold is an indicator of a seizure in this time window. Huffman bitstream is temporarily saved to the memory and/or transmitted wirelessly depending on the application needs.

Below, we summarize the compression methods used above [8, 9] and also discuss their relation to seizure detection.

2.1. Delta Encoder

Delta Encoding calculates the difference between sequential input samples to eliminate temporal redundancy and stores/transmits only the difference values (*delta*) as shown in Eq. (2). Therefore, small amplitude change between adjacent samples produces a small delta and high amplitude change between adjacent samples produces a large delta.

Delta encoding (Eq. (2)) is similar to the line-length [10] feature (Eq. (3)) used for seizure detection where N is the window size and x is the sampled input data.

$$D(k) = x(k) - x(k-1) \tag{2}$$

$$LL(n) = \frac{1}{N} \sum_{k=n-N}^{n} |x(k) - x(k-1)| \tag{3}$$

The line-length is a common feature for seizure detection. To calculate line length, the average of absolute difference between neighboring samples is calculated and the seizure decision is made when the difference between a short-term current window line-length value and a long-term previous window line-length value is greater than a predefined threshold.

Therefore, the line-length value is expected to be high when a seizure occurs. Delta encoder shows similar properties as the line length feature: For the delta encoder as shown in (2), the difference between neighboring samples is calculated. The output is near constant when the input changes linearly and the output changes randomly during a seizure. Therefore, after Huffman encoding, the CR is low for constant/slow changing data, whereas it is high for randomly changing data.

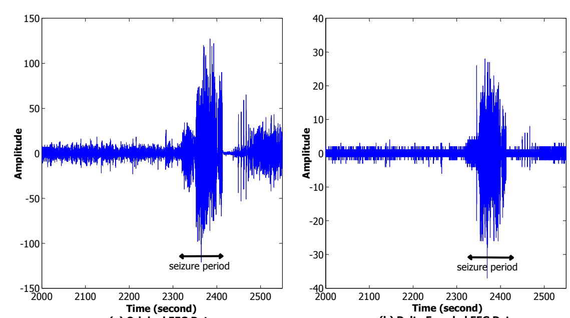

Figure 2: Delta encoding for EEG data.

An example EEG seizure data, and its delta compressed form is shown in Fig. 2. Delta encoding outputs small values consistently before the seizure onset but a random mixture of small and large values during the seizure. Finally, delta encoding outputs small values consistently after the seizure period. Therefore, we can expect that the compression ratio after Huffman encoding will be increased during seizure period and it will be decreased before and after seizure. Based on these properties, we can use compression ratio as a feature for seizure detection.

2.2. Huffman Encoder

Huffman encoder is an entropy coding for lossless data compression [9]. Huffman encoding uses variable length code according to the frequency of character. In other words, huffman encoder assigns the fewer bits for the frequently used characters and more bits are assigned for the characters that seldom used. As explained earlier, delta encoder output has near constant before a seizure and then it changes with high amplitude when seizure comes. Therefore, compression ratio of huffman encoder is also increased when seizure data is compressed.

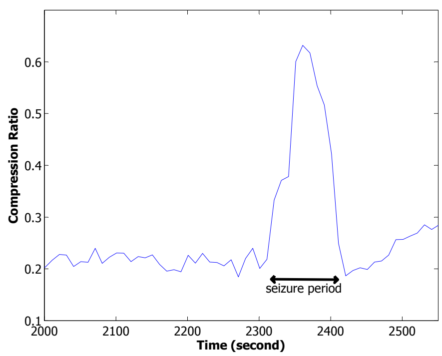

Figure 3: 10 seconds averaged CR of Seizure Data.

Fig. 3 shows 10 seconds averaged lossless compression ratio of seizure contained data in Fig. 2. The compression ratio is decreased before-seizure and then suddenly compression ratio is increased seizure data, finally compression ratio is decreased again after seizure period. We can see the huge difference in compression ratio between before-seizure and seizure data. Therefore, we can detect seizure by comparing compression ratio. We use every 1sec data stream to compress and 60sec average compression ratio is calculated for seizure detection. Finally, we compare with 1sec current compression ratio and averaging previous 60sec compression ratio for seizure detection. Seizure decision is made when the difference between the current compression ratio and the previous compression ratio is greater than a certain threshold, similar to the line-length seizure detection method.

2.3. Run-length Encoder

The optional Run length encoder (RLE), which is used for lossy compression here, compresses data by representing input data samples as data value and its continuous length when the same data value continuously and frequently is occurred. Therefore, we can get better compression performance when the input data does not change frequently. If input signal does not change fast, we may get almost constant value near zero after at the output of the delta encoding. After the quantization, it produces more zeros in a bitstream. Therefore, RLE shows better compression performance. As mentioned before, delta encoding produces nearly small constant output before seizure. Therefore, RLE can boost up the difference of compression ratio between before-seizure and seizure.

3. Results

We evaluated the compression ratio and seizure detection performance of the proposed CR-based seizure detection method using recordings from 7 patients in the CHB-MIT scalp EEG database [11]. This data contains 272 hours of recordings with 34 seizures. The data is sampled at 256 Hz. We also analyzed the power consumption of the proposed method based on the power consumption of a 16-bit microcontroller (MSP430, Texas Instruments).

Table 1: CR, Seizure Detection performance and power consumption for the proposed method.

	CR	Seizure Detection	Power Est. [32MHz]
Pre-ictal	0.27	FPh:5.55	$0.45mA$
Ictal	0.54	Accuracy:30/34	$(@3.3V)$
Post-ictal	0.32	Latency:12.32*sec*	
Entire Data	0.37		

Table 1 summarizes our findings. The average compression ratio for the entire data set is 0.37, whereas this average falls to 0.27 for the 30 seconds preceding the seizure onset (pre-ictal) and climbs to 0.54 for the 60 seconds following the seizure onset (ictal). Finally, CR falls to 0.32 for the 60 seconds after the seizure period (post-ictal).

Fig. 4 shows 1 min. averaged CR for all channels in an hour-long recording with a 2 min. seizure with onset at 18 min. For all the channels, the CR stays low before seizure, suddenly increases at seizure onset, and finally decreases again after the seizure.

The difference between the CRs of non-seizure, pre-ictal, and ictal data introduces the possibility to use CR as a seizure indicator. Seizure detection performance using CR is given in the second column in Table 1. The seizure detection accuracy is 88.2% (30/34)

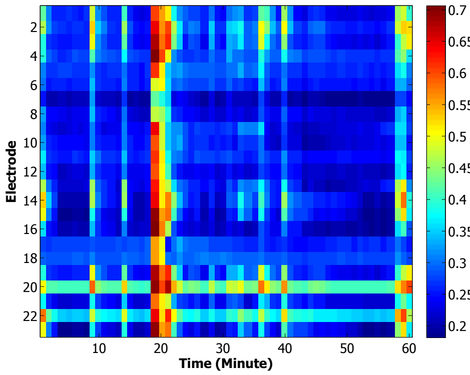

Figure 4: Compression ratio for all channels (red: high CR, blue: low CR).

with 5.55 FPh and the detection latency is 12.32 seconds. Note that the seizure detection property is a by-product of compression, and comes with no additional costs. It can be used by itself as a low-power seizure detection/compression method, or can be combined with more sophisticated methods for better seizure detection and compression.

The estimated power for this compression and detection system using MSP430 is about 0.45 mA at 32 MHz clock frequency. Since the number of operation per one channel compression is 1.05 Mcycles, we can compress up to 30 channels in real-time.

4. Discussion

The proposed algorithm misses 4 seizures out of the tested 34 seizures. One of these seizures is missed due to its very short duration (9 sec), which does not impact the CR much in its window. The remaining three seizures are detected, but they are considered missed, since their detection time is either more than 30 sec. before (1 seizure) or 30 sec. after (2 seizures) the seizure onset. In this work, we assume any seizure not detected beyond 30 sec. from the onset is considered missed.

5. Conclusion and Future Work

Wireless seizure monitoring devices should transmit and process data efficiently to minimize their power consumption. Two common tasks in such devices are compression and seizure detection, however these two operations are usually considered, separately. In this paper, we investigated the potential of merging these two operations into a single method to reduce overall power consumption, and proposed a compression-ratio-based seizure detection method, which uses readily available information from compression for seizure detection avoiding additional computation and power cost for seizure detection.

References

[1] J. Viventi, D.-H. Kim, L. Vigeland, and *et al.*, “Flexible, foldable, actively multiplexed, high-density electrode array for mapping brain activity in vivo,” *Nature Neuroscience*, vol. 14, no. 4, pp. 1599 – 1605, 2011.

[2] Y. Wongsawat, S. Oraintara, T. Tanaka, and K. Rao, “Lossless multi-channel eeg compression,” in *Circuits and Systems, Proceedings. 2006 IEEE International Symposium on*, may 2006.

[3] C. H. Chung, L.-G. Chen, Y.-C. Kao, and F.-S. Jaw, “Multichannel evoked neural signal compression using advanced video compression algorithm,” in *4th International IEEE/EMBS Conference on Neural Engineering (NER 2009)*, May 2009.

[4] T. Kim, N. Artan, J. Viventi, and H. Chao, “Spatiotemporal compression for efficient storage and transmission of high-resolution electrocorticography data,” in *Engineering in Medicine and Biology Society (EMBC), Annual International Conference of the IEEE*, Sep. 2012.

[5] A. Shoeb, A. Kharbouch, J. Soegaard, S. Schachter, and J. Guttag, “A machine-learning algorithm for detecting seizure termination in scalp eeg,” *Epilepsy and Behavior*, vol. 22, Supplement 1, no. 0, pp. S36 – S43, 2011.

[6] A. Zandi, M. Javidan, G. Dumont, and R. Tafreshi, “Automated real-time epileptic seizure detection in scalp eeg recordings using an algorithm based on wavelet packet transform,” *Biomedical Engineering, IEEE Transactions on*, vol. 57, no. 7, pp. 1639 –1651, 2010.

[7] A. M. White, P. A. Williams, D. J. Ferraro, S. Clark, S. D. Kadam, F. E. Dudek, and K. J. Staley, “Efficient unsupervised algorithms for the detection of seizures in continuous eeg recordings from rats after brain injury,” *Journal of Neuroscience Methods*, vol. 152, no. 12, pp. 255 – 266, 2006.

[8] G. Wallace, “The JPEG still picture compression standard,” *IEEE Trans. Consumer Electronics*, vol. 38, no. 1, Feb. 1992.

[9] R. Hashemian, “Memory efficient and high-speed search huffman coding,” *Communications, IEEE Transactions on*, vol. 43, no. 10, pp. 2576 –2581, oct 1995.

[10] R. Esteller, J. Echauz, T. Tcheng, B. Litt, and B. Pless, “Line length: an efficient feature for seizure onset detection,” in *Engineering in Medicine and Biology Society, Proceedings of the 23rd Annual International Conference of the IEEE*, vol. 2, 2001.

[11] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, “Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.