EOG Signal Compression Using Turning Point Algorithm

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Abstract—Electrooculography is one way to measure the electrical activity of the eyes. An electrooculogram (EOG) is the graphical representation of the electrical signal generated from eye movement. The different applications developed in the past decade based on these signals require a large amount of data to store and transmit, so compression is necessary. This paper presents a study conducted to compress EOGs using the turning point (TP) algorithm. For this purpose, electrical signals were acquired using a BlueGain EOG device, and the algorithm was implemented using MATLAB software. From this algorithm the signal was compressed and later reconstructed. The performance of the algorithm was analyzed using three parameters: compression ratio (CR), percent root-mean-square difference (PRD), and compression performance (CP). The experimental results, conducted over seven iterations of the algorithm, showed that the TP algorithm produced a fixed CR of 2:1 and a PRD of 2.9131 in its first iteration.

Keywords—compression performance (CP), compression ratio (CR), EOG compression, percent root-mean-square difference (PRD), turning point (TP) algorithm.

I. INTRODUCTION

The electrooculogram (EOG) is a record of the electrical activity of the eye, used as a diagnostic tool for pathologies in the oculomotor system [1, 2] and for sleep disturbances as part of polysomnographic (PSG) studies [3]. It can be a reliable source of commands, setting up a relationship between the direction of a gaze and an action to be performed. Because of this, several systems have been developed in the past decade in which controls are carried out according to the direction of a gaze. These systems are mainly focused on the development of human–computer interfaces to control robot arms [4] and prostheses [5] and enhance personal autonomy [6, 7].

The large amount of biomedical signal data recorded by these devices needs to be stored and transmitted efficiently at a low cost; it is necessary to reduce the data storage space while preserving significant information for signal reconstruction. This process is called data compression, and its main purpose is to transmit data in an efficient manner, reducing data from the original signal while retaining useful features and reducing the memory requirements to save the compressed signal. This is especially important for large PSG signals, typically around 8 hours of recording.

Many techniques have evolved for compressing signals. In this work, direct data compression techniques in which timerelated data are directly compressed are considered. Examples are the turning point (TP) [8-10] and fan [11] algorithms, coordinate reduction time encoding system (CORTES) [12], and amplitude zone time epoch coding (AZTEC) [13]. These techniques have been widely studied for compression of electrocardiogram (ECG) and speech signals but have not been studied for the compression of EOGs. In this study, the use of the TP algorithm was analyzed to compress EOG signals. The TP algorithm reduces the sampling rate by half compared to the input sampling rate, eliminating half the samples. It presents the easiest implementation and requires the least computation time of any standard algorithm used for data compression. The compression ratio (CR), percent root-mean-square difference (PRD), and compression performance (CP) parameters were calculated for seven iterations of the algorithm.

The paper is organized as follows: Section II introduces the proposed materials and methods, exploring the background of EOGs and the algorithm foundations. The experimental results are shown and discussed in Section III. Finally, Section IV concludes the work.

II. MATERIALS AND METHODS

A. EOG Signal Background

An EOG is obtained by measuring the potential differences between two points of the eye using a biomedical amplifier. The amplitude and bandwidth of the EOG signal are in the range of 50 to $3500 \ \mu\text{V}$ and 1 to 50 Hz, respectively [14]. In the present work, two electrodes were used to record the vertical movements: one electrode above the eyebrow and another below the lower eyelid of the right eye. A third electrode was placed at the forehead, used as a reference potential to reduce user common-mode voltage. Fig. 1 shows the electrode placement. The waveform depends on the position of the positive and negative leads. The electrodes consist of a conducting gel, embedded in the middle of a self-adhesive pad connected to the lead.

To record the signal, the commercial bioamplifier BlueGain was used [15]. Its block diagram is represented in Fig. 1. The signal is band-pass filtered with a cutoff frequency between 0.1 and 30 Hz, sampled at a frequency of 1 kHz, and digitized using a 16-bit ADC at 10 kHz. Finally, the signal is sent wirelessly to the computer via Bluetooth.

An EOG is based on saccadic eye movements that are characterized by a quick shift of gaze (of both eyes) from one point of fixation to another. Whenever there is eye movement, the differential potential result changes, related to the magnitude of rotation and its amplitude, depending on the



Fig. 1. Electrode placement and block diagram of the BlueGain device.



Fig. 2. Example of EOG signal, recorded using the BlueGain bioamplifier.

angle the eyeball moves. Whenever the eyeball looks to either point, the voltage is positive or negative (depending on electrode placement) and returns to zero when looking straight ahead [16]. Fig. 2 shows a typical waveform sent to a computer. By recording the vertical derivation of eye movements, involuntary and voluntary blinks (with 10 to 20 times greater amplitude) are also recorded.

B. Turning Point Algorithm

These are the reasons for selecting the TP algorithm over other direct data compression techniques: As mentioned before, the TP algorithm was originally developed to reduce the sampling frequency of an ECG signal by half because this signal is normally oversampled at four to five times faster than the highest frequency present [8]. The TP algorithm reduces the sampling rate by half, selectively saving the peaks and valleys (the turning points), that is, only the samples that contain important information are saved. Basically, this data reduction algorithm downsamples [17]. Since the algorithm produces nonzero residuals, it is lossy, and an exact reconstruction at the decoder end cannot be made. There may be tolerable loss of information in the reconstructed signal. Furthermore, the TP algorithm can be applied in real-time applications.

The algorithm processes three samples of the signal at a time. It stores the first sample and assigns it as the reference x_0 . The next two consecutive samples are x_1 and x_2 . The algorithm retains either x_1 or x_2 , depending on which sample preserves the turning point (i.e., slope change) of the original signal. A turning point occurs when the slope changes from positive to negative or vice versa. Therefore, to decide which sample is saved, (1) is used on the computed slope values:

$$sign(x) = \begin{cases} 0 & x = 0\\ 1 & x > 0\\ -1 & x < 0 \end{cases}$$
(1)

The steps of the TP algorithm can be summarized as follows:

- 1) Load the EOG signal x(t).
- 2) Take the first three samples and check for the condition: $sign((x_1 x_0) \times (x_2 x_1)) < 0$.
- 3) If the above condition is correct, then x_1 is stored; otherwise x_2 is stored.

Table I shows the possible arrangement of three consecutive samples. If the slope is zero, the above condition produces a zero result. Positive or negative slopes yield +1 or -1, respectively. In each frame, the black point retains the

TABLE I. REPRESENTATION OF THE CONDITIONS TO CONSIDER IN THE TP ALGORITHM

Pattern	$sign(x_1 - x_0)$	$sign(x_2 - x_1)$	Condition result	Saved sample
°°	1	1	1	<i>x</i> ₂
0 • 0	1	-1	-1	<i>x</i> ₁
0 • 0	1	0	0	<i>x</i> ₂
0.0	-1	1	-1	<i>x</i> ₁
° ° •	-1	-1	1	<i>x</i> ₂
0.0	-1	0	0	<i>x</i> ₂
00	0	1	0	<i>x</i> ₂
••	0	-1	0	<i>x</i> ₂
00•	0	1	0	<i>x</i> ₂

slope of the three samples considered. The algorithm saves this sample as reference x_0 for the next iteration. It then processes the next two samples, assigns them to x_1 and x_2 , and repeats the process.

The TP algorithm performs a fixed CR of 2:1, and the reconstructed signal resembles the original signal with some distortions.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The EOG signals were recorded in our laboratory using the BlueGain device. Each signal lasted approximately five and a half minutes and was 9,987 kB in size. In the computer, the EOG signal is first preprocessed by normalization and mean removal to guarantee that all significant coefficients are less than one. This allows reducing the number of bits needed to represent each coefficient. Zero padding is also carried out to reduce the reconstruction errors at both ends of the compressed signal [18].

To reconstruct the compressed signal the signal is interpolated, increasing the sample rate by a factor of two. Fig. 3 shows the original, the compressed, and the reconstructed signal performances after an iteration of the TP algorithm. The CR obtained is 2:1, but the algorithm can be performed on the already compressed signal to duplicate the CR with each iteration. However, after the second compression, some data may be lost since the signal overlaps itself. Therefore, the TP algorithm is typically limited to two iterations, that is, a CR of 4:1. As can be seen in Fig. 3, the TP algorithm can reduce the amount of data to be stored and transmitted without losing important information. More iterations of the algorithm were evaluated to find an optimal compression strategy for EOG. The effectiveness of each iteration was quantified in terms of the following parameters [19]:

• CR: determines how much gain reduction is applied by running the algorithm: The ratio of the original data to compressed data, without considering factors such as bandwidth, sampling frequency, or noise level. It is expressed by (2):

$$CR = \frac{N_{\text{original}}}{N_{\text{compressed}}}$$
(2)

where $N_{original}$ and $N_{compressed}$ are the number of samples in the input and compressed signal, respectively.



Fig. 3. a) Original; b) compressed, and c) reconstructed signal performances of an iteration of the TP algorithm.

Therefore, the number of samples in the compressed signal is half compared to the number of samples in the input signal. The higher the CR, the smaller the size of the compressed file.

• Compression factor (CF): the reciprocal of the CR expressed by (3):

$$CF = \frac{1}{CR}$$
(3)

• CP: measured with the help of CF and expressed by (4):

$$CP(\%) = (1 - CF) \times 100$$
(4)

The computed CR is 2 for all iterations over the signal. So the computed CF is 0.5, and the evaluated CP is 50% of each iteration.

• PRD: a measure of error loss. This measure evaluates the distortion between the original and the reconstructed signal. PRD is calculated by (5):

PRD (%) =
$$100 \times \sqrt{\frac{\sum_{i=1}^{n} (\text{OrigSignal}(i) - \text{RecSignal}(i))^{2}}{\sum_{i=1}^{n} (\text{OrigSignal}(i))^{2}}}$$
 (5)

The residual generated by the reconstruction process must be considered to determine the acceptability of the reconstructed signal, that is, the difference between the reconstructed signal and the original signal given by the PRD value. The reconstructed EOG signal can thus be quite acceptable despite a high residual [8].

Table II presents the values obtained in each iteration of the algorithm. The objective was to obtain a high-quality reconstruction of EOG at low bit rates and with acceptable distortion levels. It is worth noting the significant reduction in the size of the signal in the first two iterations, maintaining a reasonable PRD value. Despite the high PRD value obtained by a CR of 128:1, the reconstructed signal maintained the waveform, as can be seen in Fig. 4. On the other hand, the TP algorithm provides a better PRD over ECG signals, for which this algorithm has been designed. A PRD of 0.15 was obtained over an ECG signal sampled at 360 Hz with also a CR of 2:1 in its first iteration [9].

TABLE II. CR, CP, PRD, AND COMPRESSED SIGNAL SIZE OBTAINED BY PERFORMING SEVEN ITERATIONS OF THE ALGORITHM

CR	СР	PRD Compressed Signal Size (kB)	
2:1	50%	2.9131	3,032
4:1	75%	8.3092	1,483
8:1	87.5%	16.3596	736
16:1	93.75%	31.2874	363
32:1	96.88%	60.4022	177
64:1	98.44%	111.1699	88
128:1	99.22%	217.2776	44



Fig. 4. a) Original; b) compressed, and c) reconstructed signal performing seven iterations of the TP algorithm.

As mentioned previously, TP is a lossy algorithm, being an assumed loss of information in the reconstructed signal. It was observed in the references that were applied in speech signals sampled at 20 kHz, the hearing quality of the compressed signal is much better than the hearing quality of the original signal [10]. In this case, the CP obtained is 50 % in all speech signals analyzed and can also be observed from the EOG signal.

IV. CONCLUSION

The problem of limited operational bandwidth for EOGbased assistive and medical systems can be solved by preprocessing the EOG signal before transmission. An EOG data compression algorithm could also solve archival problems, reducing the amount of data to be stored and analyzed without losing the main information content. This can be seen by comparing the signal size before and after compression.

Results show that each iteration of the TP algorithm on the EOG signal always produces a CR of 2:1, without significant distortions in the waveform of the reconstructed signal. If more compression is necessary, the same algorithm could be applied to the compressed signal. However, as the number of iterations increases, errors in the reconstructed signal increase considerably. Results show that the TP algorithm produces a good signal fidelity and good reduction ratio, which can be used for real-time transmission.

Future work should analyze other algorithms that operate outside the time domain, such as transformation and extraction methods for efficient compression of EOG data. Moreover, additional statistical parameters need to be used for evaluating the performance of the algorithms in EOG compression and carrying out an exhaustive comparative study of the best signal compression techniques.

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