Performance Analysis of Hybrid Lossy/Lossless Compression Techniques for EEG Data

Madyan Alsenwi¹, Tawfik Ismail² and Hassan Mostafa³

¹Faculty of Engineering, Cairo University  
²National Institute of Laser Enhanced Science, Cairo University, Egypt  
³Center for Nanoelectronics and Devices, AUC and Zewail City of Science and Technology, Egypt

Abstract—Long recording time, large number of electrodes, and a high sampling rate together produce a great data size of Electroencephalography (EEG). Therefore, more bandwidth and space are required for efficient data transmission and storing. So, EEG data compression is a very important problem in order to transmit EEG data efficiently with fewer bandwidth and storing it in a less space. In this paper, we use the Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) which are lossy compression methods in order to convert the randomness EEG data to high redundancy data. Therefore, adding a lossless compression algorithm after the lossy compression is a good idea to get a high compression ratio without any distortion in the signal. Here, we use Run Length Encoding (RLE) and Arithmetic Encoding which are lossless compression methods. Total times for compression and reconstruction (T), Compression Ratio (CR), Root Mean Square Error (RMSE), and Structural Similarity Index (SSIM) are evaluated in order to check the effectiveness of the proposed system.

I. INTRODUCTION

Electroencephalography (EEG) is an electrophysiological monitoring technique to record electrical activity within the brain. It is typically noninvasive, with the electrodes placed in the scalp. In the medical applications, a group of sensors are placed over or inside the human body. These sensors are used to collect several EEG signals then transmit the collected data to an external station for analyzing diagnosing. The main problems during the transmission process are to minimize the transmission time with a limitation of the channel capacity and to save more power.

The compression techniques are one of the best solutions to overcome the limitation of the channel capacity and power consumption. Data compression is the process of converting an input stream of data into another smaller data stream in size. There are two types of compression techniques, lossless and lossy. In the lossless compression, the original data can be reconstructed from the compressed data without any distortion. However, this technique limits the compression ratio (CR). In the lossy compression, high CR can be achieved, but some of the original data can be loosed, which may lead a non perfect reconstruction.

The randomness in the EEG signal makes the compression of EEG data is a difficult [1]. Therefore, high CR cannot be obtained with lossless techniques. Thus, lossy compression techniques are used with an accepted level of distortion.

Several works are focused on the EEG data compression [2]. Paper [1] considered the use of DCT algorithm for lossy EEG data compression. By using the DCT only, we are unable to achieve a high CR. Paper [3] considered a compression algorithm for ECG data composed from DCT, RLE, and Huffman encoding. High CR can be achieved in this algorithm, but this algorithm consumes a long time for compression and reconstruction processes. Paper [4] considered a comparative analysis by three transform methods, DCT, Discrete Wavelet Transform (DWT), and Hybrid (DCT+DWT) Transform. A high distortion can be occurred in the reconstructed signal, since DCT and DWT both are a lossy algorithms.

The rest of this paper is organized as follows. Section II discusses EEG compression techniques. DCT, DWT, RLE and Arithmetic Encoding are introduced in this section. Section III introduces the implementation of the proposed system and performance measures. Section IV discusses the simulation results. Finally, Section V concludes the paper.

II. DATA COMPRESSION TECHNIQUES

In this section, an overview on the data compression techniques is introduced. The data compression techniques can be classified into two approaches: Lossless and Lossy Compression [5], [6]. Some of the Lossless and Lossy compression techniques, which we use it here, are given below:

A. Discrete Cosine Transform (DCT)

DCT is a type of transformation methods which converts a time series signal into frequency components. DCT concentrates the energy of the input signal in the first few coefficients and this is the main feature of DCT. Therefore, DCT is widely used in the field of data compression.

Let \( f(x) \) is the input of DCT which is a set of N data values (EEG samples) and \( Y(u) \) is the output of DCT which is a set of N DCT coefficients. For N real numbers, the one dimensional DCT is expressed as follows [1], [7], [8]:

\[
Y(u) = \sqrt{\frac{2}{N}} \alpha(u) \sum_{x=0}^{N-1} f(x) \cos\left(\frac{\pi(2x + 1)u}{2N}\right) \quad (1)
\]

where

\[
\alpha(u) = \begin{cases} 
\frac{1}{\sqrt{2}}, & u = 0 \\
1, & u > 0
\end{cases}
\]

where \( Y(0) \) is the DC coefficient and the rest coefficients are referred to as AC coefficients. The \( Y(0) \) coefficient contains...
with Haar function defined as [4], [11]:

\[ f(x) = \sqrt{\frac{2}{N}} \alpha(u) \sum_{u=0}^{N-1} Y(u) \cos\left(\frac{(2x + 1)u}{2N}\right) \]  \hspace{1cm} (2)

Most of the N coefficients produced by DCT are small numbers or zeros. These small numbers usually go down to zero.

**B. Discrete Wavelet Transform (DWT)**

In DWT, the input signal is decomposed into low frequency part (approximation) and high frequency part (details) Fig. 1. Decomposition a signal into different frequency bands is suitable for data compression which we can study each component with a resolution matched to its scale [9], [10].

In this paper, we use the DWT with Haar basis function, which is a simple DWT basis function, because it has less complexity and gives accepted performance. There are two coefficients for every two consecutive samples \( S(2m) \) and \( S(2m+1) \) in DWT with Haar function defined as [4], [11]:

\[ C_A(m) = \frac{1}{\sqrt{2}} [S(2m) + S(2m+1)] \]  \hspace{1cm} (3)

\[ C_D(m) = \frac{1}{\sqrt{2}} [S(2m) - S(2m+1)] \]  \hspace{1cm} (4)

where \( C_A(m) \) is the approximation coefficient and \( C_D(m) \) is the details coefficient. We can notice from equations (3, 4) that calculating \( C_A(m) \) and \( C_D(m) \) is equivalent to pass the signal through first order low-pass and high-pass filters with sub-sampling factor of 2 and normalized by \( 1/\sqrt{2} \).

**C. Run Length Encoding (RLE)**

RLE is a type of lossless compression. The idea of RLE is to take the consecutive repeating occurrences of a data value and replace this repeating value by only one occurrence followed by the number of occurrences (Fig. 2). This is most useful on data that contains many such runs [3], [7], [12].

**D. Arithmetic Coding (AC)**

Arithmetic coding is a type of entropy encoding. Unlike other types of entropy encoding, such as Huffman coding, which replace each symbol in the message with a code, the entire message is replaced with a single code in arithmetic coding.

First, the input file is read symbol by symbol and the Arithmetic algorithm starts with a certain interval. The probability of each symbol is used to narrow the interval. Specifying a new interval requires more bits, so the arithmetic algorithm designed such that a low-probability symbol narrows the interval more than a high-probability symbol in order to achieve compression. Therefore, the high-probability symbols contribute fewer bits to the output [13], [14], [15].

**III. IMPLEMENTATION AND PERFORMANCE MEASURES**

This section introduces the implementation of the proposed algorithm and the performance measures.

**A. Implementation**

The proposed system consists of two main units: compression unit and decompression unit.

1) **Compression Unit**: The first step in this unit is reading the EEG data file, and transform it by DCT or DWT (according to user selection). After that, thresholding step is applied to get a high redundancy in the transformed data. In this step, values below the threshold value are set to zero. The number of zero coefficients can be increased or decreased by varying the threshold value. Therefore, the accuracy of the reconstructed data can be controlled. Transformation and thresholding steps together increase the probability of redundancies in the transformed data. Finally, if we use RLE or Arithmetic Encoding (according to the user selection), we will get a high compression ratio due to the high redundancy in the transformed data (Fig. 3, Table I).

1) **Reconstruction Unit**: First, the compressed data is decoded using inverse RLE or inverse Arithmetic encoding, according to the selection in the compression unit, then the inverse DCT or inverse DWT is applied, also according to the selection in the compression unit, in order to reconstruct the EEG data (Fig. 3, Table I).

**B. Performance Measures**

1) **Root Mean Square Error (RMSE)**: The RMSE is used to test the quality of the reconstructed signal. RMSE measures how much error between two signals as follows:

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y'_i)^2}{n}} \]

where \( y_i \) and \( y'_i \) are the reconstructed and original signals, respectively.

The Normalized RMSE (NRMSE) is defined as the following:

\[ \text{NRMSE} = \frac{\text{RMSE}}{y_{\text{max}} - y_{\text{min}}} \]
TABLE I: Compression and Reconstruction Algorithm

\[
\begin{align*}
\text{Data} & \leftarrow \text{EEG Data} \\
\triangleright \text{Lossy Compression} \\
\text{if } \text{DCT is Required} \text{ then} \\
& \quad \text{TransData} \leftarrow \text{DCT(Data)} \\
\text{else} \\
& \quad \text{TransData} \leftarrow \text{DWT(Data)} \\
\text{end if} \\
\triangleright \text{Thresholding} \\
& \quad \text{Thr} \leftarrow \text{ThresholdValue} \\
& \quad [\text{SortedData}, \text{index}] \leftarrow \text{sort(abs(Data))} \\
& \quad i \leftarrow 1 \\
& \quad \text{for} \ \text{LengthOfData} \ \text{do} \\
& \quad \quad \text{if } \text{abs}(x(i)/x(1)) > \text{Thr} \text{ then} \\
& \quad \quad \quad i \leftarrow i + 1 \\
& \quad \quad \quad \text{continue} \\
& \quad \quad \text{else} \\
& \quad \quad \quad \text{break} \\
& \quad \quad \text{end if} \\
& \quad \text{end for} \\
& \quad \text{TransData(index}(i + 1: \text{end})) \leftarrow 0 \\
\triangleright \text{Lossless Compression} \\
\text{if } \text{RLE is Required} \text{ then} \\
& \quad \text{CompressedData} \leftarrow \text{RLE(TransData)} \\
\text{else} \\
& \quad \text{CompressedData} \leftarrow \text{Arithm(TransData)} \\
\text{end if} \\
\triangleright \text{Reconstruction} \\
\text{if } \text{RLE is used} \text{ then} \\
& \quad \text{DecData} \leftarrow \text{IRLE(CompressedData)} \\
\text{else} \\
& \quad \text{DecData} \leftarrow \text{IArithm(CompressedData)} \\
\text{end if} \\
\text{if } \text{DCT is used} \text{ then} \\
& \quad \text{ReconstructedData} \leftarrow \text{IDCT(DecData)} \\
\text{else} \\
& \quad \text{ReconstructedData} \leftarrow \text{IDWT(DecData)} \\
\text{end if} \\
\end{align*}
\]

where \(y_{\text{max}}\) and \(y_{\text{min}}\) are the maximum and minimum values in signal \(y\), respectively.

2) Compression Ratio (CR): The second performance measure, which we use it in this paper, is the CR, which is defined as:

\[
CR = \frac{\text{OriginalData} - \text{CompData}}{\text{OriginalData}} \times 100
\]

3) Compression and Reconstruction Time (T): The third performance measure is the time (T), which is the total time of compression process and reconstruction process.

4) Structural Similarity index (SSIM): The last performance measure is the Structural Similarity index (SSIM) [16] which is defined as the following:

\[
\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}
\]

where \(\mu_x, \mu_y, \sigma_x, \sigma_y\), and \(\sigma_{xy}\) are the means, standard deviations, and cross-covariance for signals \(x,y\). \(C_1\) and \(C_2\) are the regularization constants [16].

IV. SIMULATION AND RESULTS

The performance of the proposed system is studied using Matlab and it’s run on Intel(R) Core(TM) i3 CPU 2.27GHz, 4 GB RAM. The size of EEG data, which we use it here in the simulation, is 1 MB.

Fig. (4) shows the CR of each case with different values of Normalized RMSE. The value of RMSE can be changed by varying the threshold value. Fig. (4) shows that the case of DCT with RLE has the highest CR. This due to the compacting property of DCT which causes high redundancy in the transformed data and facilitates the use of RLE. Also, the case of DCT with Arithmetic Encoding has a good CR compared to other cases. In addition to the good CR, Arithmetic coding exports data in the binary form. So, we don’t need to use analog to digital converter in case of using arithmetic coding. Fig. (5) shows the total time of compression and reconstruction processes with normalized RMSE. We notice from this figure that the case of DWT only has the smallest time since the implementation of DWT is simple (just Low pass filter and High pass filter). Conversely, Arithmetic coding consumes more time compared to the other techniques and this due to the complexity of Arithmetic coding. Also, Fig. (5) shows that the case of DWT with Arithmetic coding consumes time more than in case of DCT with Arithmetic despite the DWT consumes time less than DCT. This because that DCT produces redundancy in the data higher than DWT and this redundancy facilitates the use of Arithmetic coding and make it fast.

Fig. (6) shows the CR with SSIM. The results in this figure exactly the inverse of the results in Fig. (4) since the SSIM inversely proportion to the RMSE. We can control the value
probability of redundancy. Finally, a lossless compression, value are replaced by zero. The resulting signal has a high threshold is applied and all coefficients below the threshold EEG signal into basic frequency components. After that, a proposed. The lossy compression techniques, DCT and DWT, consumes small time. Conversely, DWT with Arithmetic is consumes time. Conversely, DWT with RLE is the best since it has the highest CR, and less time compared with other cases (DCT with Arithmetic, DWT with RLE, DWT with Arithm).

V. CONCLUSION

In this paper, a compression algorithm for EEG data is proposed. The lossy compression techniques, DCT and DWT, are applied to transform the high randomness time series EEG signal into basic frequency components. After that, a threshold is applied and all coefficients below the threshold value are replaced by zero. The resulting signal has a high probability of redundancy. Finally, a lossless compression, of SSIM by varying the threshold value. Finally, the final comparison between all techniques according to CR and time is shown in Fig. (7). Figure (7) shows the DCT with RLE is the best since it has the highest CR and consumes small time. Conversely, DWT with Arithmetic is the worst since it has low CR and consumes long time.

REFERENCES