Hybrid DCT/RLE Compression Technique with Data Segmentation for Electroencephalography Data

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Abstract—Long recording time, large number of electrodes, and high sampling rate together produce a large 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 less bandwidth and storing it in a less space. The objective of this paper is to develop an efficient algorithm for EEG compression. Firstly, the EEG signal is segmented into N segment, and then transformed through Discrete Cosine Transform (DCT). The transformed coefficients are passed through a thresholding process and the values below the threshold are set to zero. Finally, the resulting coefficients are coded using the Run-Length Encoding (RLE) scheme. The EEG signal can be recovered by an inverse process. Total time for compression and reconstruction (T), Compression Ratio (CR) and Percentage Root Mean Error Difference (PRD) are evaluated in order to check the effectiveness of the proposed algorithm. Simulation results show that there is a good improvement in the compression time in case of using compression with data segmentation.

I. INTRODUCTION

Currently, one of the most important issues in the medical applications is transmission of biomedical signals through communication channels. As an example of this issue is transmission of the EEG signals. Recording the EEG signals for several hours generates a large amount of EEG data. Therefore, data compression techniques are required for efficient communication purposes.

Data compression techniques can be classified into lossy and lossless compression. In the lossless compression, the original data can be perfectly reconstructed without any distortion. In the lossy compression, some of the data can be loosed and this causes a non-perfect reconstruction.

Compression of the EEG signal is a difficult task due to the randomness in the EEG signal. Therefore, it is difficult to achieve a high CR with lossless compression techniques [1].

In this paper, an efficient lossy compression algorithm based on DCT and RLE is developed. The original EEG data is segmented into N segments before starting the compression process in order to reduce the compression and reconstruction time (T) and increase the efficiency of the developed algorithm.

Several works are focused on the EEG data compression [1]. The work in [2] considered the use of DCT algorithm for lossy EEG data compression. By using the DCT only, we are unable to achieve a high CR. While in [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. The study in [4] is based on 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 lossy algorithms.

The rest of this paper is organized as follows. Section II discusses EEG compression techniques, DCT and RLE is briefly described in this section. Section III introduces the implementation of the proposed system and performance measures. Section IV presents 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. DCT, which is type of lossy compression, and RLE, which is type of lossless compression, are presented here.

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 [2], [4], [5], [6]:

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

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...
the mean value of the original signal.
Inverse DCT takes transform coefficients $Y(u)$ as input and converts them back into time series $f(x)$. For a list of n DCT coefficients, the inverse transform is expressed as follows [7]:

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

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

B. Run Length Encoding (RLE)

RLE is a type of lossless compression. The idea of RLE is to take the consecutive repeating occurrences of certain data value and replace this repeating value by only one occurrence to take the consecutive repeating occurrences of certain data numbers or zeros. This is most useful on data that contains many such runs [3], [8], [9].

III. IMPLEMENTATION

This section introduces the implementation of the proposed algorithm and the performance measures. The compression without and with data segmentation is introduced here to show the difference between the two cases.

A. DCT with RLE

First, we propose a system consists of two main units: compression unit and reconstruction unit as shown in Fig. 2. Algorithm (1) show the compression and reconstruction process for DCT with RLE.

1) Compression Unit: The first step in this unit is reading the EEG data file, and transform it by DCT. After that, thresholding step is applied to get a high redundancy in the transformed data. In this step, values below the threshold 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, high compression ratio achieves due to the high redundancy in the transformed data by using RLE [10].

1) Reconstruction Unit: First, the compressed data is decoded using inverse RLE. Then the inverse DCT is applied in order to reconstruct the EEG data.

| Algorithm 1 Compression and Reconstruction Algorithm in Case of DCT with RLE |
| --- |
| ▶ Compression Unit |
| Data ← EEG Data |
| ▶ DCT Compression |
| TransData ← DCT(Data) |
| ▶ Thresholding |
| Thr ← ThresholdValue |
| [SortedData, index] ← sort(abs(Data)) |
| i ← 1 LengthOfData abs(x(i)/x(1)) > Thr |
| i ← i + 1 |
| continue |
| break |
| TransData(index(i + 1 : end)) ← 0 |
| ▶ RLE Compression |
| n ← 1 |
| d(n) ← TransData(1) |
| c(n) ← 1 |
| i ← 2 i ≤ LengthOfData TransData(i - 1) = TransData(i) |
| c(n) ← c(n) + 1 |
| n ← n + 1 |
| d(n) ← TransData(i) |
| c(n) ← 1 |
| CompressedData ← [d, c] |
| ▶ Reconstruction |
| ▶ RL Decoding |
| d ← CompressedData(:, 1) |
| c ← CompressedData(:, 2) |
| RLDec ← [] |
| i ← 1 i ≤ LengthOfData |
| RLDec = [RLDec d(i) * ones(1, c(i))] |
| ▶ Inverse DCT |
| ReconstructedData ← IDCT(RLDec) |

B. Data Segmentation and Compression

The first step in this case is reading the EEG data and segment it into N sample. Each sample is taken every $T_s$ time as shown in Fig. 3. We can reduce the total time (compression and reconstruction) by decreasing $T_s$. However, the $T_s$ value must be maintain upper threshold value to guarantee that each unit completes the current segment before arriving a new segment according to the following condition:

$$T_s = \max(T_{DCT}, T_{thr}, T_{RLE}, T_{IRLE}, T_{IDCT})$$  \hspace{1cm} (3)

where $T_{DCT}$ is the DCT time, $T_{thr}$ is the thresholding time, $T_{RLE}$ is the RLE time, $T_{IRLE}$ is the inverse RLE time and $T_{IDCT}$ is the inverse DCT time. Therefore, the minimum sampling time $T_{min}$ can be obtained from the following equation:

$$T_{min} = \max(T_{DCT}, T_{thr}, T_{RLE}, T_{IRLE}, T_{IDCT})$$  \hspace{1cm} (4)

This algorithm achieves the smallest compression and reconstruction time if $T_s = T_{min}$. After that, the segmented...
data will go through the compression unit and reconstruction unit respectively. The final step is combining the reconstructed data which is the inverse process of the data segmentation. Algorithm (2) show the compression and reconstruction process in case of compression with data segmentation.

C. Performance Metrics

All performance metrics which used in this paper are presented here.

1) Percentage Root Mean Difference (PRD): Which is measurement of the distortion between the original signal and the reconstructed signal. PRD can be defined as [11], [12], [13]:

\[
PRD = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y'_i)^2}{\sum_{i=1}^{n}y_i^2}} \times 100
\]  

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

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

\[
CR = \frac{\text{Original Data} - \text{Comp Data}}{\text{Original Data}} \times 100
\]  

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

\[
T = T_{\text{comp}} + T_{\text{reconst}}
\]

where \(T_{\text{comp}}\) is the total compression time and \(T_{\text{reconst}}\) is the total reconstruction time and can be defined as the following:

\[
T_{\text{comp}} = T_{\text{DCT}} + T_{\text{thr}} + T_{\text{RLE}}
\]

\[
T_{\text{reconst}} = T_{\text{IRLE}} + T_{\text{IDCT}}
\]

Therefore, the total time can be defined as the following:

\[
T = T_{\text{DCT}} + T_{\text{thr}} + T_{\text{RLE}} + T_{\text{IRLE}} + T_{\text{IDCT}}
\]

IV. SIMULATION RESULTS

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

Fig. 4 shows the CR with different values of PRD in case of compression without data segmentation. The value of PRD can be changed by varying the threshold value.

Fig. 5 shows the total time of compression and reconstruction processes with PRD in case of compression without data segmentation. If the threshold value is increased, more coefficients will be set to zero. Therefore, the PRD will increase and the time will decrease.

Fig. 6 shows the total time with different values of N in case of compression with data segmentation. We can get a high reduction in the total time if the original EEG data is segmented. The minimum value of T can be achieved if we put \(N = 200\), as shown in this figure.

Finally, a comparison between the compression without segmentation and with segmentation \((N = 200)\) regarding to CR is shown in fig. 7. For the same PRD, the compression with segmentation has a higher CR than compression without segmentation.

V. CONCLUSION

In this paper, a compression algorithm for EEG data is proposed. First, the EEG data is segmented into N segment then each segment is compressed using DCT. After that, all the coefficients below the threshold are set to zero. Finally, the resulting data is compressed using RLE. The inverse process is applied in order to recover the original EEG data. CR, PRD and T are evaluated to check the performance of the proposed system. The case of compression with data segmentation has a higher CR, and less time compared with compression without segmentation.

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Algorithm 2 Compression and Reconstruction Algorithm with Data Segmentation

▷ Data Splitter
   \( N \leftarrow \text{NumberOfRequiredSamples} \)
   \( L \leftarrow \text{LengthOfEEGData} \)
   \( sp \leftarrow \text{floor}(L/N) \) \( k \leq N \) \( k = 1 \)
   \( \text{Data} \leftarrow \text{EEGData}(1 : sp) \)
   \( \text{initial} \leftarrow (k - 1) * sp + 1 \)
   \( \text{finals} \leftarrow k * sp \)
   \( \text{Data} \leftarrow \text{EEGData} \left( \text{initial} : \text{finals} \right) \)
   \( \text{vector} \leftarrow \text{EEGData} \left( k * sp + 1 : L \right) \)
   \( \text{Data} \leftarrow [\text{Data vector}] \)

▷ DCT Compression
   \( \text{TransData} \leftarrow \text{DCT(Data)} \)

▷ Thresholding
   \( \text{Thr} \leftarrow \text{ThresholdValue} \)
   \( [\text{SortedData}, \text{index}] \leftarrow \text{sort(abs(Data))} \)
   \( i \leftarrow 1 \)
   \( \text{LengthofData} \) \( \text{abs}(x(i)/x(1)) > \text{Thr} \)
   \( i \leftarrow i + 1 \)
   continue
   break
   \( \text{TransData(index}(i + 1 : \text{end})) \leftarrow 0 \)

▷ RLE Compression
   \( n \leftarrow 1 \)
   \( d(n) \leftarrow \text{TransData}(1) \)
   \( c(n) \leftarrow 1 \)
   \( i \leftarrow 2 \) \( i \leq \text{LengthOfData} \) \( \text{TransData}(i - 1) = \text{TransData}(i) \)
   \( c(n) \leftarrow c(n) + 1 \)
   \( n \leftarrow n + 1 \)
   \( d(n) \leftarrow \text{TransData}(i) \)
   \( c(n) \leftarrow 1 \)
   \( \text{CompressedData} \leftarrow [d, c] \)

▷ Reconstruction

▷ RL Decoding
   \( d \leftarrow \text{CompressedData}(:, 1) \)
   \( c \leftarrow \text{CompressedData}(:, 2) \)
   \( \text{RLDec} \leftarrow [\text{]} \)
   \( i \leftarrow 1 \) \( i \leq \text{LengthOfData} \)
   \( \text{RLDec} = [\text{RLDec} \cdot d(i) \cdot \text{ones}(1, c(i))] \)

▷ Inverse DCT
   \( \text{ReconstructedData} \leftarrow \text{IDCT(RLDec)} \)

▷ Data combining
   \( \text{FinalOutput} \leftarrow [\text{FinalOutput}, \text{ReconstructedData}] \)
Fig. 7: CR versus PRD in case of N=1 and N=200

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