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A Comparative Study Using DCT, Delta Modulation, and Double Shift Coding for Compressing Electroencephalogram Data

Hend A. Hadi[1], Loay E. George[2]
[1]General Education Directorate of Baghdad-Karkh-3, Ministry of Education, Baghdad, Iraq
[2]University of Information Technology and Communication (UoITC), Baghdad, Iraq

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Abstract

Storing, transferring, and processing high-dimensional electroencephalogram (EGG) signals is a critical challenge. The goal of EEG compression is to remove redundant data in EEG signals. Medical signals like EEG must be of high quality for medical diagnosis. This paper uses a compression system with near-zero Mean Squared Error (MSE) based on Discrete Cosine Transform (DCT) and double shift coding for fast and efficient EEG data compression. This paper investigates and compares the use or non-use of delta modulation, which is applied to the transformed and quantized input signal. Double shift coding is applied after mapping the output to positive as a final step. The system performance is tested using EEG data files from the CHB-MIT Scalp EEG Database. Compression Ratio (CR) is used to evaluate the compression system performance. The results are encouraging when compared with previous works on the same data samples.

Keywords: *EEG, Compression, DCT, Double shift coding, Delta Modulation, Mapping to Positive, Histogram, Compression Ratio.*

دراسة مقارنة باستعمال تحويل الجيب تمام المتقطع و تعديل دلتا والمشفر الزاحف المزدوج لضغط بيانات التخطيط الكهربائي للدماغ

هند عبدالامير هادي*[1] , لؤي ادور جورج[2]
[1]وزارة التربية، المديرية العامة لتربية بغداد الكرخ الثالثة، بغداد، العراق
[2]جامعة تكنولوجيا المعلومات والاتصالات، بغداد، العراق

الخلاصة

يعد موضوع تخزين ونقل ومعالجة إشارات التخطيط الكهربائي للدماغ (EGG) تحديًا بالغ الأهمية. ان الهدف من ضغط اشاره الدماغ EEG هو إزالة البيانات الفائضة في الإشارة. يجب أن تكون الإشارات الطبية مثل إشارات (EEG) ذات جودة عالية للتشخيص الطبي. يستعمل هذا البحث نظام ضغط مع متوسط الخطأ التربيعي (MSE)القريب من الصفر بناءً على تحويل جيب التمام المتقطع (DCT) والمشفر الزاحف المزدوج لضغط بيانات EEG بشكل سريع وفعال. يبحث هذا البحث ويقارن بين استعمال أو عدم استعمال تعديل دلتا، والذي يتم تطبيقه على الإشارة المحولة باستعمال ال DCT والمكممة. يتم تطبيق المشفر الزاحف المزدوج بعد تحويل الإخراج إلى قيم موجبة كخطوة أخيرة. تم اختبار أداء النظام باستعمال ملفات بيانات EEG من قاعدة بيانات CHB-MIT Scalp EEG. تم استعمال معيار نسبة الضغط (CR) لتقييم أداء نظام الضغط. لقد كانت النتائج مشجعة عند مقارنتها بنتائج الأعمال السابقة المنفذه على عينات البيانات نفسها.

*Email: hend_amir2007@yahoo.com

Introduction

Electroencephalogram produces electrical activities of the human brain in one-dimensional signals recorded by electrodes, which are placed on the scalp. EEG signals are used in brain-computer interface (BCI) and brain disease diagnostic in telemedicine systems [1].

Also, EEG is used commonly in different fields such as neuroscience, neuro-linguistics, cognitive science, cognitive psychology, and psychophysiology. The EEG data must be stored and transmitted in many cases, so it must be of adequate size. In many cases such as in intensive care, which requires recording the patient's EEG for several hours or days to observe any abnormal activity. As a result, a huge amount of data is generated and may be stored and transmitted. This consumes a large amount of storage and high bandwidth for transmission [2]. Therefore, many works in this field have made experiments to achieve the best compression ratio with zero or near-zero loss for the data since these data are sensitive and very important for researchers and physicians [3] [4].

Shaw et al. [4] proposed various lossless single and multichannel compression methods of EEG data, based on Huffman coding, arithmetic coding, Markov predictor, linear predictor, context-based error modeling, and multivariate auto-regression (MVAR). In addition, they proposed a high compression algorithm for multichannel EEG such as general MVAR and a modified context-based error modeling. The performance of the compression algorithm shows a high relative compression ratio (RCR) of 704% on average, and in some cases, it reaches up to 83.06%.

Chen et.al. [5], proposed a lossless EEG compression circuit based on an effective Very-Large-Scale Integration (VLSI) circuit design to improve the efficiency of EEG signal transmission over WBAN. The proposed scheme is based on an adaptive fuzzy predictor, a voting-based scheme, and a tri-stage entropy encoder. A pipelining method was included to improve the performance of the proposed scheme.

Hejrati et al. [1], proposed a compression system based on channel clustering. Their system consists of two stages using inter-channel and intra-channel correlations. In the first stage, the arithmetic coding is used to code the centroid of each cluster; where the channels are grouped in various clusters after applying a differential pulse code modulation (DPCM) as a preprocessing step and extracting intra-channel correlation. The second stage is based on arithmetic coding to compress the difference between the centroid and the data of channels in each cluster.

Sriraam [6] proposed using neural network predictions and the concept of correlation dimension (CD) to build a lossless EEG compression system. Non-linear dynamic parameter CD is used to characterize the irregular EEG signals; it is a measure of the correlation of the EEG samples. The CD value of each segment is calculated after the input EEG signals are first divided into 1-second segments. After that, the segments with closer CD values were grouped into blocks. This arrangement improved the accuracy of the predictor and as a result, fewer bits were required for transmission.

Srinivasan et al. [7], investigated different lossless compression techniques for electroencephalogram (EEG) signals. They consider a simple pre-processing method, where the EEG signal is organized in a (2-D) matrix before the compression stage. A two-stage coder to compress the EEG matrix, (SPIHT) for a lossy coding layer and (arithmetic coding) for a residual coding layer were discussed in this work.

Wongsawatt et al.[8], took advantage of the inter-correlation among the EEG channels using the Karhunen-Loeve transform to propose a lossless multi-channel compression system. In addition, they minimized the temporal redundancy using an integer time-frequency transform.

Many works considered shift coding as an encoding step for the compression system. Hassan et al. [9], proposed an adaptive shift coding as an encoding step to reduce the bits required to represent the color image in the proposed compression system.

Hashim & Ali [10], proposed another shift coding optimizer to find the optimal two code word sizes vital to represent the small and large sequence values in their compression system.
George et al. [11], encoded the data of a selective image encryption system using a proposed hybrid shift.
Ibrahim et al. [12], proposed an improved entropy encoder for a new high-performance lossy compression system. Farhan et al. [13], proposed two shift-coding techniques for an image compression system, the first technique uses 4 bits to represent a byte whose value is less than 15 while the other one checks the value of the byte to give it either 4 bits or 7 bits.
The following is an outline of this paper. Section 2 displays the proposed compression system. Section 3 illustrated the metrics used to measure the efficiency of the compression system. Section 4 contains the experimental results and shows a comparison of the conducted results with previous works. While Section 5 is the conclusion and future suggestions concerning the research area.

The Proposed Compression System

In this section, the proposed EEG compression system is displayed. In our previous work, a lossless EEG compression system is produced and tested on the Motor Movement EEG dataset [14], the proposed system is proper for integral signals. In this work, another EEG compression system is produced and tested to solve the compression system of EEG with floating-point numbers. In the EEG compression system, the EEG signal is subdivided into 1×64 sub-bands, and then DCT is applied to each sub-band to compute DCT coefficients. Then quantization step is used to construct the quantized DCT coefficients, which are going to be reduced using delta modulation and encoded using double shift coding with minimum total bits. Figure-1 shows the general representation of the proposed system.

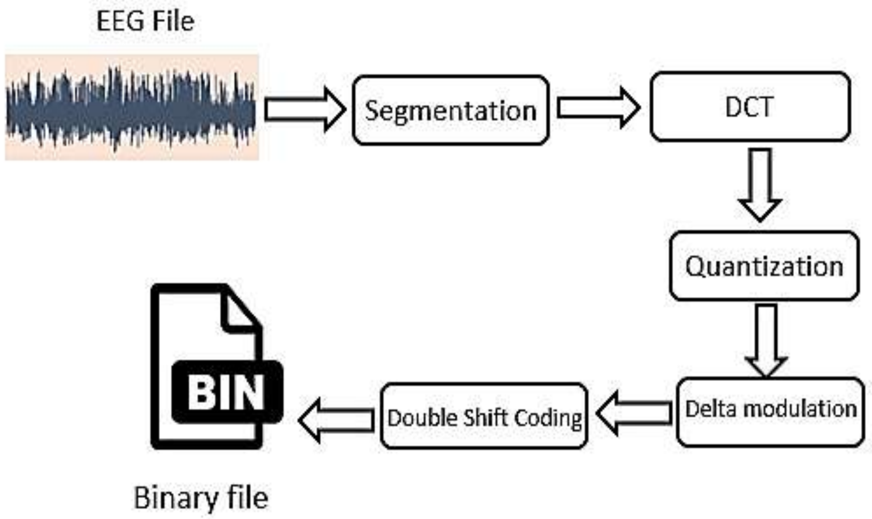

Figure 1- The proposed EEG compression system

Segmentation

The EEG signal of length m is divided into non-overlapping blocks of length 64. Each block is input to the DCT transform. The segmentation reduces system complexity because processing short-length block is faster than when processed long signals, therefore accelerating the compression and decompression process [12]. Figure (2) explains the EEG signal segmentation into N blocks.

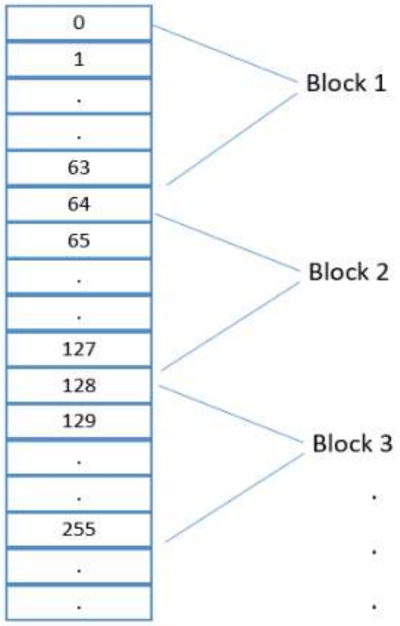

Figure 2-EEG Segmentation Step

Discrete Cosine Transform (DCT)

DCT transformation method is used to convert a time series signal into frequency coefficients [15]. DCT is used commonly in the data compression field because it concentrates the energy of the converted signal in the beginning coefficients; this is the key feature of DCT [16]. The forward DCT is determined using Eqs. (1a) and (1b) [17] [18]:

$$C(u) = \alpha(u) \sum_{i=0}^{N-1} S(i) \cos\left(\frac{u\pi(2i+1)}{2N}\right) \quad (1a)$$

Where C(u) is the u^{th} Coefficient of DCT, N is signal length, S(i) is the i^{th} sample of the input signal, and u=0,…, N-1; and

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{2}} & if\ u = 0 \\ 1 & if\ u \neq 0 \end{cases} \quad (1b)$$

The inverse DCT is used in the decompression stage to reconstruct the original signal and determines by Eq.(2) [17]:

$$S(u) = \alpha(i) \sum_{i=0}^{N-1} C(i) \cos\left(\frac{\mathrm{u}\pi(2\mathrm{i}+1)}{2\mathrm{N}}\right) \quad (2)$$

Where S (u) is the u^{th} element of the retrieved signal, and C(i) is the i^{th} element of the transformed signal.

Non-Uniform Quantization

Quantization maps input from a continuous set of values (such as the real numbers) to a discrete set (such as the integers), rounding, and truncation are common examples of quantization [19]. In quantization, insignificant data is removed and the number of bits that are required to represent and store the values of the DCT coefficients is reduced [20] [21]. During the non-uniform quantization, every AC coefficient is divided by a corresponding quantization value (Q_{stp}), which is generated using Eq. 4, while the DC coefficient is divided by a constant value (DC_{stp}). The non-uniform quantization is applied to produce a quantized vector using Eqs. (3) and (4):

$$QDCT(i) = round(\frac{DCT(i)}{Qstp(i)}) \quad (3)$$

$$Q_{stp}(i) = Q_0 + Q_1 * i \quad (4)$$

Where i is the i^{th} element in the DCT array. For an effective quantization performance, a different set of values were tested to obtain the optimal values of Q_0, Q_1, and DC_{stp}.

Delta Modulation (DM)

DM is a special and simple form of differential pulse code modulation (DPCM), in which the difference between two adjacent samples is calculated to reduce the signal values using Eq.(5) and (6) [11]:

$$DM(i) = S(i) - S(i-1) \qquad if\ i > 0 \quad (5)$$

Where DM (i) is the i^{th} item of delta modulation array, S is the transformed signal, and

$$DM(0) = S(0) \quad (6)$$

Eq. (6) is used to save the first value in the input signal to retrieve the original signal in the decompression stage [22]. In the proposed system, the input signal is segmented to blocks of 64 samples. After applying DCT and Quantization to each block, then new blocks are assembled based on the index, i.e. the zero index of all QDCT arrays are assembled in block (0) and so on until filling the last block (63) with all index 63 of all QDCT arrays; as shown in Figure-3. After that, the obtained blocks are passed to the delta modulation and the encoder for final bit optimization.

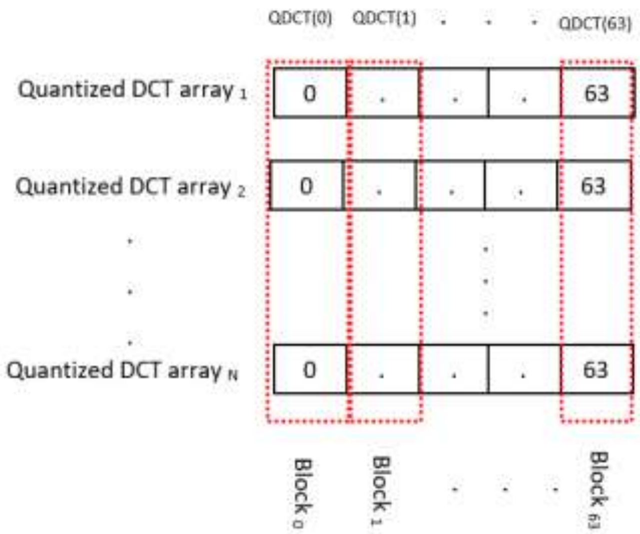

Figure 3- The quantized DCT coefficients combined into blocks.

Double Shift Coding

The input to the encoder must be positive values to prevent coding complexity so; mapping to a positive process is applied to the DM array. All DM values are mapped to a positive using Eq. (7) [22]:

$$X_i = \begin{cases} 2X_i & if\ X_i > 0 \\ -2X_i - 1 & if\ X_i < 0 \end{cases} \quad (7)$$

Where X_i is the i^{th} element in the MD array. According to the above equation, the positive values will be even, while the negative values will be odd to recognize them in the decompression process [21].

After mapping to positive, the histogram of the new positive array is calculated (His array) to find the maximum value to be used in the encoder optimizer to determine short, medium, and long code words [23].

The double shift coder is applied as the final step in the compression system to encode the output with a minimum number of bits to obtain high compression gain.

After calculating the histogram and defining the maximum value in the positive array the encoder optimizer is applied to find out the three code-words lengths (short, long code-words, tail for the reminder) to encode variant lengths of the input values. The encoder optimizer is improved to take into account the statistical attributes of the incoming stream.

The optimal code-words lengths should satisfy the criteria: "they lead to the minimum total number of bits (T_{bits}) needed to represent all sequence elements values" [21]. The encoder uses double shift keys {0, 10, and 11} as key flags for the short code words, long code words, and a tail for Reminder respectively. The total number of required bits is determined in Algorithm1. The process of encoder optimizer is implemented in Algorithm 1, where Max is the maximum value in His array, OptBits is the optimal total bits, Sbits is the short code word, Lbits is the long code word, and Rbits is the tail for the reminder. After determining the optimal values of Sbits, Rbits, and Lbits, then the double shift coding is applied to save the output into a binary file as shown in Fig.1.

Algorithm: Double shift coding optimizer
Input: His (), Max // His () is the histogram array, and Max is the maximum value in the histogram array. **Output:** Sbits, Lbits, Rbits, and Opt Bits // short, long, and reminder code-words

Step1: Start
Step2: Declare MaxBit, Flg, I, J, R, R1, R2, Remain, K, Sm1, Sm2, Sm3
Step3: MaxBit ← Log (Max + 1) / Log (2)) // Find maximum bits using logarithm function
Step4: Flg ← 0 // flag variable
/// Find optimal code-words
Step5: Initialize I=2 //Starts with two bits
Step5.1. : R1 ←Pow (2, I) // Where Pow is the power function
Step5.2. : Sm1 ← 0
Step5.3. : Initialize R=0
Sm1 ← Sm1 + His[R]
Increment R
Step5.4. : Repeat steps until R>R1-1
Step5.5. : Initialize J=2
Step5.5.1 : R2 ← R1 + Pow (2, J)
Step5.5.2 : Remain ← Max - R2;
Step5.5.3 : If (Remain >= 0) Then
  Step5.5.3.1 : K ← Log (Remain + 1) / Log (2)
  Step5.5.3.2 : Sm2 ← 0
  Step5.5.3.3 : Initialize R ← R1
Sm2 ← Sm2 + His[R]
Increment R
  Step5.5.3.4 : Repeat the steps until R> R2 – 1
  Step5.5.3.5 : Sm3 ← 0
  Step5.5.3.6 : R ← R2
Sm3 ← Sm3 + His[R]
Increment R
  Step5.5.3.7 : Repeat the steps until R> Max
  Step5.5.3.8 : Tbits ← Sm1*(I + 1) + Sm2*(J + 2) + Sm3 * (K + 2)
  Step5.5.3.9 : If ((Flg == 0) || (Flg > 0 && OptBits > Tbits)) Then
OptBits ← Tbits
Sbits ← I

Rbits ← J
Lbits ← K
Flg ← 1
Step5.5.3.1 : End If
Step5.5.4 : End If //////////Remain
Step5.5.5 : Increment J
Step5.6. : Repeat the steps until J >=MaxBit
Step5.7. : Increment I
Step6: Repeat the steps until I >=MaxBit
Step7: End

The reverse of the earlier mentioned steps is applied to decompress and rebuild the EEG file as shown in Figure-4.

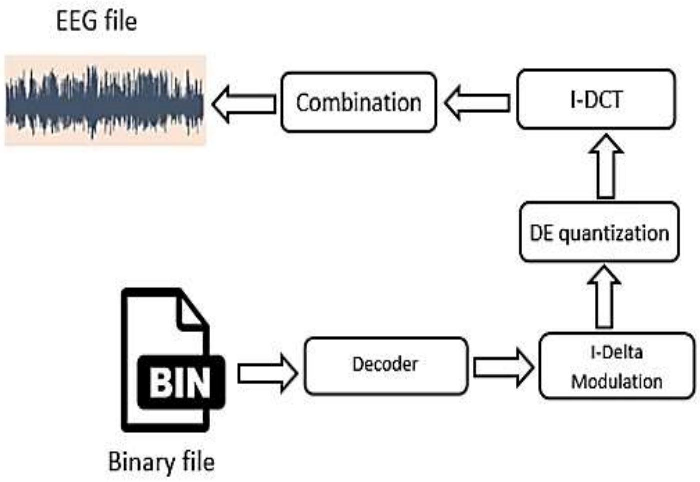

Figure 4-the Decompression system

Performance Metrics

All performance metrics used in this research are explained in this section.

A. Compression Gain (CG):

The first performance metric is the compression gain and it is calculated by Eq. (8):

$$CG = 10 \times \ log_{10}\left(\frac{\text{Reference Size}}{\text{Compressed Size}}\right) \tag{8}$$

Where the reference size is the size of the input sequence. The unit of the compression gain is the percent log ratio and is represented by percentage [9].

Compression Ratio (CR)

The second compression performance metric is the CR. It is essential to know how many details can be discarded from the input data in order to keep only significant and essential information of the original data in the process of data compression. The Compression Ratio (CR) is defined by Eq. (9) [24] [25]:

$$CR = \frac{UnCompressed\ Size}{Compressed\ Size} \tag{1}$$

Experimental Results

To evaluate the performance of the proposed system, the experimental tests are achieved using CHB-MIT dataset [26]. This dataset comprises 23 EEG channels recorded from pediatric subjects with seizures at the “Children’s Hospital in Boston, Massachusetts” [1]. Each channel of this dataset was sampled at 256 Hz. The recordings of five subjects in this dataset are used in this paper. Table-1 shows the number of samples in each EEG channel of the five files.

Table 1-The number of samples of the EEG channel for each file

File Name	Number of samples
Ch01	921600
Ch02	921600
Ch03	921600
Ch04	3685888
Ch05	924160

The conducted study discusses the use of delta modulation with DCT. The test results showed that the system performance without delta modulation is better than that with delta modulation.

Table (2) shows the comparison of using delta modulation and the effect of some tested quantization values on the performance of the proposed compression system, which is applied on the Ch05 file, Q_0 and Q_1, are the quantization parameters for AC coefficients. DCstp is the quantization parameter for DC coefficients. In Figure-5, the curves show the general performance of the system in the two cases (i.e., with delta modulation and without delta modulation).

Table (3) shows the attained CR, CG, and MSE of the five files, when the DCstp=2, Q_0=2, and Q_1=0.01. While Table-4 shows the processing time of DCT, quantization, and coding steps in seconds for the five tested EEG files.

Taking into account the specifications of the computer lab top that used in the run tests are Intel® Core ™ i5-2450M CPU with (4GB) RAM, the operating system is windows-10 (64bit), and the development programming language is Microsoft Visual C#.

Table 2-The effect of using delta modulation and some tested quantization values.

Quantization Parameters			With Delta Modulation		Without Delta Modulation	
DC_{stp}	Q_0	Q_1	MSE	CR	MSE	CR
2	1	0.01	0.15	4.91	0.15	5.31
6	1	0.01	0.19	4.90	0.19	5.34
2	1	0.02	0.23	5.13	0.23	5.55
6	1	0.02	0.28	5.12	0.28	5.58
2	2	0.01	0.44	5.59	0.44	6.08
3	2	0.01	0.45	5.60	0.45	6.09
4	2	0.01	0.46	5.61	0.46	6.10
5	1	0.01	0.18	4.90	0.47	6.11
6	2	0.01	0.48	5.62	0.48	6.11
6	2	0.02	0.61	5.77	0.61	6.28
6	1	0.05	0.63	5.59	0.63	6.11
6	2	0.03	0.76	5.91	0.76	6.42
6	1	0.06	0.78	5.72	0.78	6.24
6	2	0.04	0.92	6.04	0.92	6.54
6	3	0.01	0.92	6.12	0.92	6.66

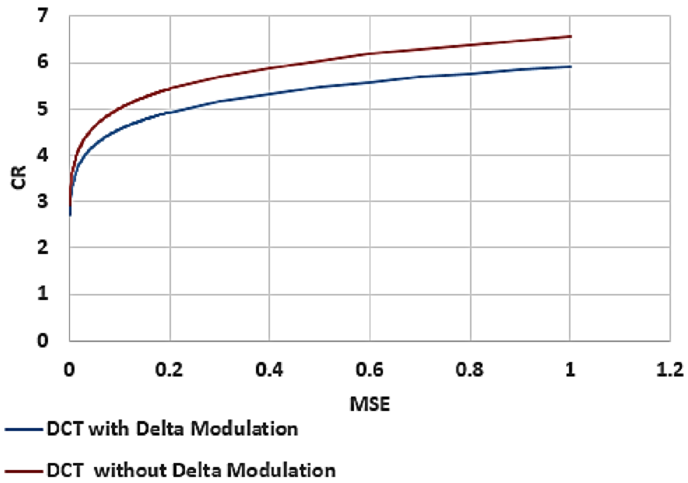

Figure 5-The performance of the proposed system with DM and without DM.

Table 3-The CR and CG of the tested files, when the DCstp=2, Q0=2, and Q1=0.01.

Subject	CR		CG	MSE
Ch01	6.13		83.68%	0.44
Ch02	6.02		83.39%	0.44
Ch03	7.13		85.97%	0.42
Ch04	5.77		82.68%	0.92
Ch05	6.08		83.56%	0.44

Table 4-The processing time of DCT, quantization, and double shift coding steps in second

File	DCT	Quantization	Coding
Ch01	7.19	1.19	0.04
Ch02	7.13	1.17	0.08
Ch03	7.16	1.16	0.05
Ch04	30.78	20.81	0.04
Ch05	8.11	1.36	0.11

Comparison with Related works

The CR of the proposed method is compared with some existing methods on the CHB-MIT dataset; the results are shown in Table-5. The proposed system showed CR better than the existing method with MSE near zero.

Table 5-The comparison with the related works in term of CR

Subject	[1]	[3]	[6]	[8]	Proposed
Ch01	2.04	1.93	1.7	1.63	**6.13**
Ch02	1.61	1.68	1.67	1.38	**6.02**
Ch03	1.87	1.86	1.83	1.55	**7.13**
Ch04	2.02	1.94	1.84	1.62	**5.77**
Ch05	1.9	1.77	1.61	1.45	**6.08**

Conclusions and Future Work

In this paper, a comparative study of EEG compression scheme based on delta modulation and DCT is presented using double shift coding. A good compression ratio was attained when the system was applied to some EEG files of the CHB-MIT EEG dataset.

The use of Delta modulation with DCT does not improve the performance. The system performance without DM showed an overall enhancement in system performance measures. Double shift coding finds the optimal number of bits to represent the input sequence.

As a future extension to the introduced system, a discrete wavelet transform can be tested and used instead of DCT to decrease the system complexity and improve the system performance because the discrete wavelet transform holds complexity less than DCT and runs faster.

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