A Telemedicine based on EEG Signal Compression and Transmission

Sawsan D. Mahmood
College of Engineering, University of Diyala, Iraq.

Maha A. Hutaihit
College of Engineering, University of Diyala, Iraq.
E-mail: mahaabbashutaihit@uodiyala.edu.iq

Tamara A. Abdulrazaq
College of Engineering, University of Diyala, Iraq.

Azmi Shawkat Abdulbaqi
University of Anbar, College of Computer Science and Information Technology, Iraq.

Nada Nasih Tawfeeq
Department of Electrical Engineering, Tikrit University, Tikrit City, Iraq.

Received May 23, 2021; Accepted August 24, 2021
ISSN: 1735-188X
DOI: 10.14704/WEB/V18SI05/WEB18270

Abstract

As a result of RLE and DWT, an effective technique for compressing and transmitting EEG signals was developed in this study. With low percent root-mean-square difference (PRD) values, this algorithm's compression ratio (CR) is high. The life database had 50 EEG patient records. In clinical and research contexts, EEG signals are often recorded at sample rates between 250 and 2000 Hz. New EEG data-collection devices, on the other hand, may record at sampling rates exceeding 20,000 Hz. Time domain (TD) and frequency domain (FD) analysis of EEG data utilizing DWT retains the essential and major features of EEG signals. The thresholding and quantization of EEG signal coefficients are the next steps in implementing this suggested technique, followed by encoding the signals utilizing RLE, which improves CR substantially. A stable method for compressing EEG signals and transmission based on DWT (discrete wavelet transform) and RLE (run length encoding) is presented in this paper in order to improve and increase the compression of the EEG signals. According to the proposed model, CR, PRD, PRDN (normalized percentage root mean square difference), QS (quality score), and SNR (signal to noise ratio) are averaged over 50 records of EEG data and range from 44.0% to 0.36 percent to 5.87 percent to 143 percent to 3.53 percent to 59 percent, respectively.

Keywords

Signal Compression, Electro Encephalopathy (EEG), Savitzky–Golay Filter (SG Filter).

Introduction

Since a long time, developing countries have been the biggest medical challenge in the world. Healthy rural areas provided the best opportunities for attracting professionals and diverse medical facilities. A telemedicine proved a strong base for rural regions in this regard. The term of telemedicine is a technological application for communication for medical data transmission and receiving and consulting between patients and specialists for healthcare in remote rural areas.

Through telemedicine, medical data can be sent remotely from remote areas to the appropriate doctor's premises and vice versa. After analyzing a medical data received from patients, sensitive medical consultations can be sent from caregivers to the remote areas in order to obtain appropriate healthcare for patients. By utilizing telemedicine, the people in the rural regions can be can benefited by caregivers (doctors and specialists). Recently, chronic diseases, (such as encephalopathy), are the first cause of death in the world and rising exponentially. This is a caused by a great concern to caregivers as brain experts are unavailability in those remote rural areas. This trouble can be solved by utilizing a telemedicine app. Utilizing telemedicine, the data of EEG can be sent /received from rural areas to encephalopathy caregivers centers.

For better health monitoring of encephalopathy patients, caregivers can send and received a medical consultation to the remote regions after received and analyzed an EEG data. The EEG can be defined by electrophysiological signals caused by the human brain. One of the essential obstacles of better transmission via telemedicine is a huge continuous EEG data. To decrease the size of EEG data, A compression techniques can be employed. EEG data compression causes data to be transmission efficiently via telemedicine.

Fig. (1) below, show the various electrodes locations of EEG signals acquisition.

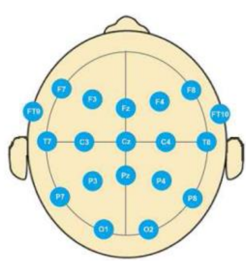


Figure 1 Electrodes locations of EEG signals acquisition

The Quality on-Demand Compression Assessment

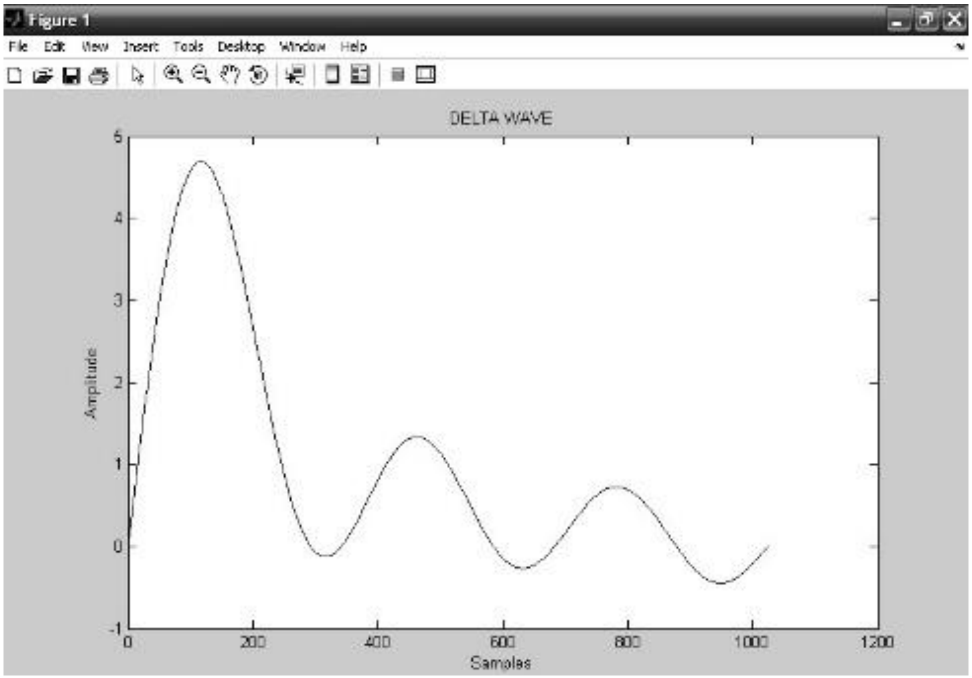
Decrease in quality of the signal can be utilized to increase compression and vice versa. Good quality of the decoded signal is clearly sacrificed for a significant degree of compression. It is necessary for experts on the receiving end to change specific settings connected with compression algorithm according to their quality interests while utilizing applications of telemedicine. To define quality-on-demand, there are two variables, namely bits per sample (BPS) and PRD. An on-demand compression strategy for EEG signals utilizing DWT and RLE is described in this paper. Four metrics, namely SNR, PRD, PRDN, QS, and CR, are utilized to quantify the fidelity of the EEG reconstructed signals (RecSig). Utilizing a two-stage lossless compression method for EEG signal compression has proven helpful. What the predictor does is compute the current value of a sample utilizing its past samples, and then transmit just the error (signal residues), which are generally lower, and the size of the original samples. They both emulate symmetrical prediction in some manner, but they do so in different ways. Start by sending initial header information and a specified number of sample values to begin utilizing the prediction technique to restore the original input, structural units are added to the expected values at the receiver's end. Providing the RecSig has the expected diagnostic features, error signals can be delivered based on certain threshold values, followed by quantification, to achieve optimum compression. Even more compression efficiency can be achieved by utilizing a second-stage arithmetic entropy encoder. Signal quality might be compromised in order to obtain higher compression, and vice versa. Accordingly, the compression method was devised in order to provide an EEG signal suitable for clinical diagnosis at CR and PRD. To establish a better balance in clinical evaluation between CR and PRD, the threshold and quantification impact must be taken into account. Utilizing effective low-bandwidth for transmission and reception in the telemedicine field, one may be certain of the diagnostic quality of reconstructed EEGs (Rec-EEG). When compared to other approaches, it appears that the suggested scheme provides respectable results (as shown in Table 3).

Related Works

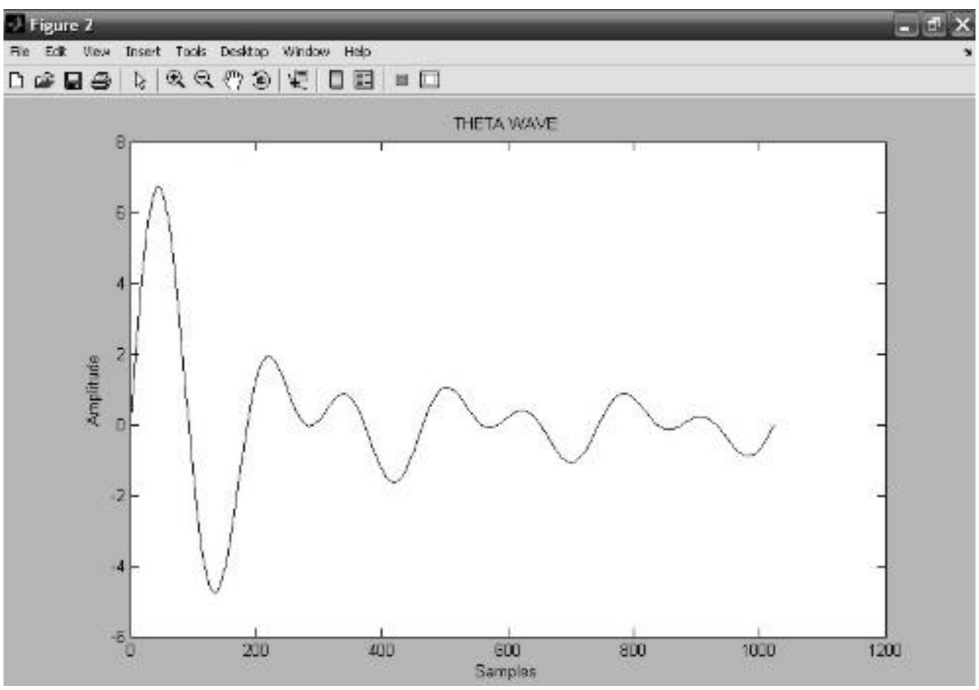
Authors working on EEG signal compression are interviewed to ensure that good and sophisticated applications with optimal operation are carried out in order for the article to meet its criteria. For the optimal compression for brain signals, a comparison of several approaches is made, as well as the transition between them.

There was a presentation on biosignal compression by Sangjoo Lee, Jungkuk Kim, and Myoungho Lee (SangJoon Lee, Jungkuk Kim and Myoungho Lee, 2011). It focused on real-time biosignal techniques that enable e-health services. A real-time compression and transmission algorithm (Comp/Trans algorithm) is included in the work of the main author. According to this article, the algorithm it proposes has the best performance when compared to other algorithms. For the near-loss compression of the EEG data, N. Sriraam and C. Eswaran (Sriraam and Eswaran, 2008), presented a compression presentation of linear and artificial neural network performance. For example, the proposed near loss-free method allowed for a real-time transmission of off-line EEG signals to a remote location while utilizing less bandwidth (Sriraam, 2011) N. Sriraam took a problem technique and utilized artificial neural network prediction to get the greatest compression result possible In order to assess and quantify the Rec-EEG signal, metrics such as PRD, SNR, cross-correlation, and power spectral density are utilized. For significant information, the RecSig can be maintained utilizing low-value PRD and single-layer perception when compared to lossless techniques, it gives the best compression results. Four researchers (Pai et al., 2012) have shown a low bit rate transmission method: Yu Ting Pai; Fan Chieh Cheng; Shu Ping Lu; and Shanq-Jang Ruan. While the compression ratio remains high, the stuffing bit may be reduced dramatically. When it comes to advancements in energy-saving communications and high-quality transmissions, the names Tao Ma and Pradhumna Lalshrestha, Michael Hempel, Dongming Peng, Hamind Sharif and Hsiao Hwa Chen (Tao Ma et al., 2012) have been cited. There is a proposed technique to reduce the transmission bits while maintaining the same compression ratio (CR). For the study and upcoming IEEE standard, M. Somasundram and R. Shivakumar have compiled an analysis of the security-related scenarios and probable consequences. As a result of this study, it was shown that widely stated security outcomes still have limitations that require more investigation (Security in Wireless Local Area Networks, 2018). A new and efficient high-performance lossless EEG compression utilizing WT and ANN predictors is presented by N.S. (HE, 2010). When EEG signals in the time domain and transformed-domains are not sparse, Z.Z. and co-workers (Zhang et al., 2013) suggest to utilize the structure of block sparse Bayesian learning, which has better efficiency to other current compressed sensing methods. For single or multichannel EEG compression, the EZW technique by D.D. et al. (Correlative Analysis of EZW and SPIHT Compression Algorithms using Sevenlets Wavelet Technique, 2020) has been found to be efficient, as it allows for progressive encoding that may be halted at any time and at any bit rate. A innovative and straightforward preprocessing approach of organizing EEG in matrix form before compression is presented by S.U. et al. (Abdulai Sawaneh, 2018). By utilizing frequency transformation and parameter extraction methods, R.M. [11] has developed a high-performance hybrid multichannel EEG compression technique (Guy Lysmos and Hanoune, 2020). WT followed by AC (arithmetic coding) on residuals improves EEG lossless compression, according to S.C. and colleagues

(Amin, Yusoff and Ahmad, 2020). On the basis of DCT frequency spectrum and Huffman-coding properties, K. et al. The numerous types of EEG waves are shown in fig. (2). EEG wave types are illustrated in the following figures (1 to 5) and table 1.



(a)



(b)

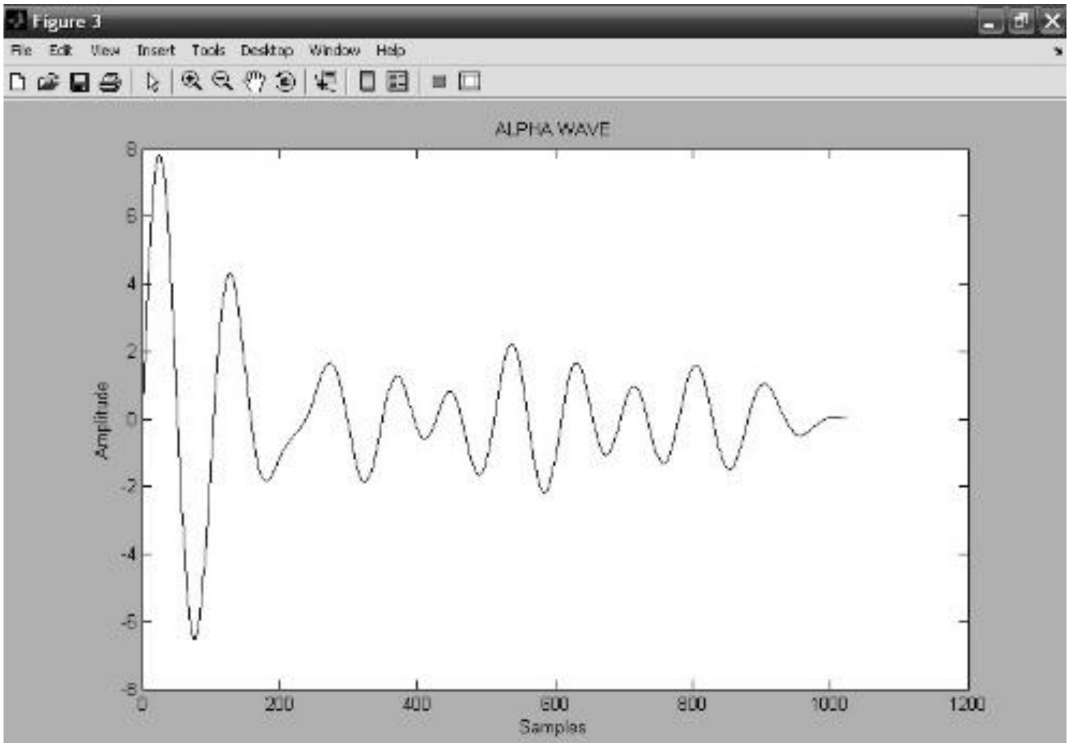


Figure 3
File Edit View Insert Tools Desktop Window Help
ALPHA WAVE
Amplitude
Samples
(c)

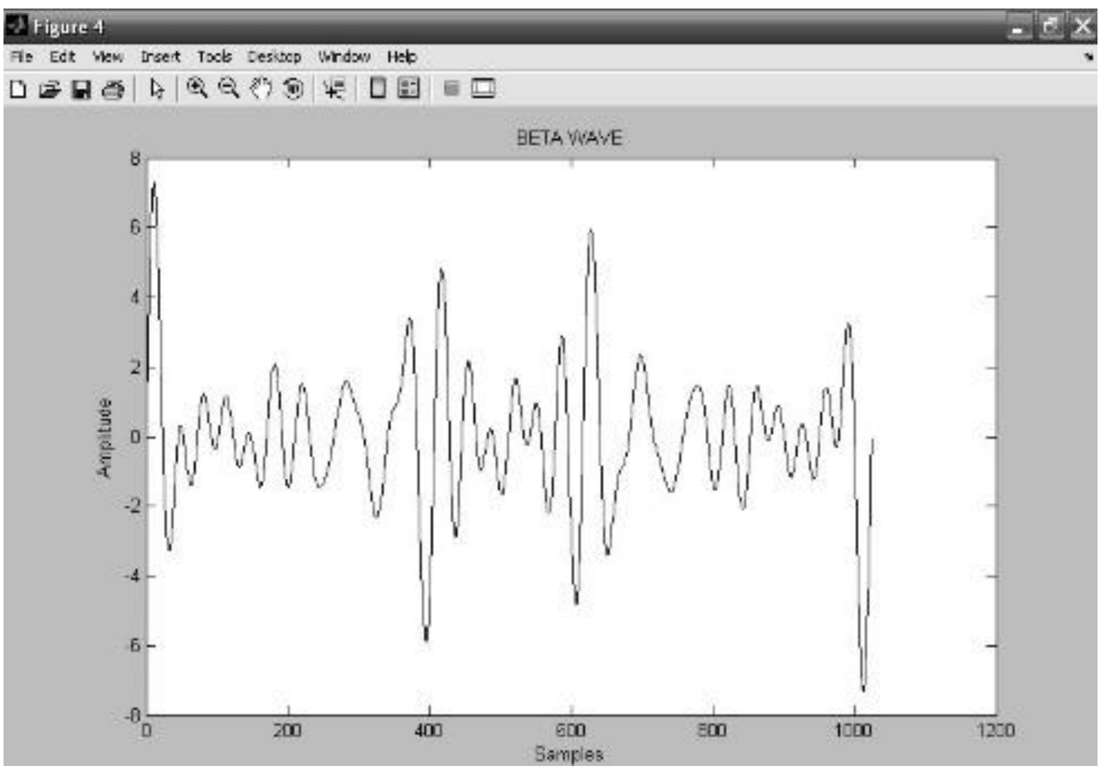
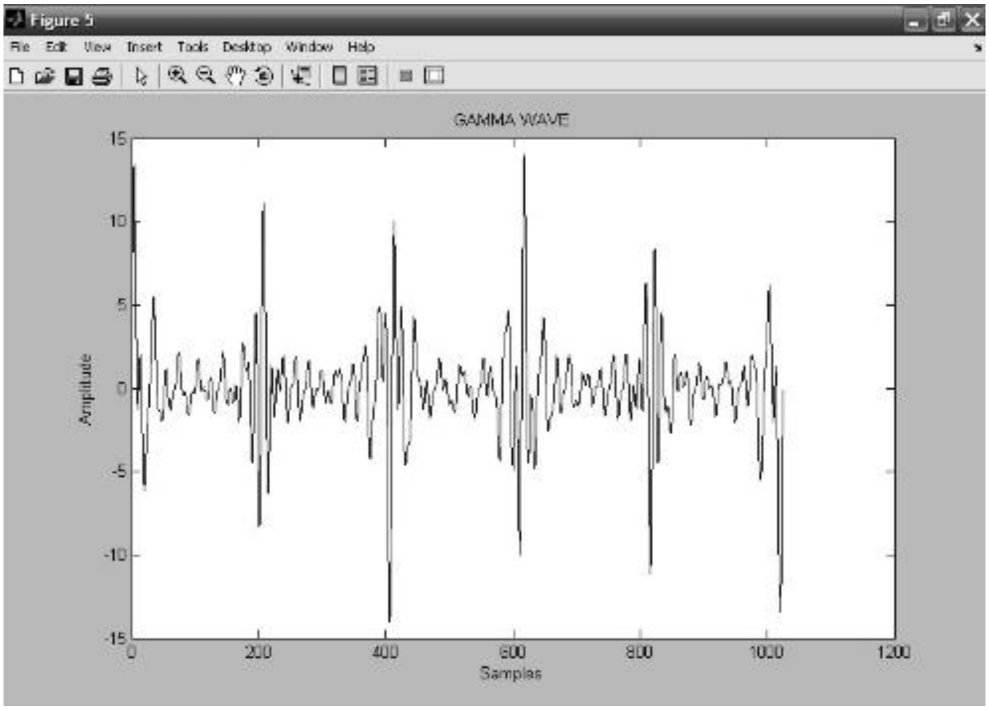
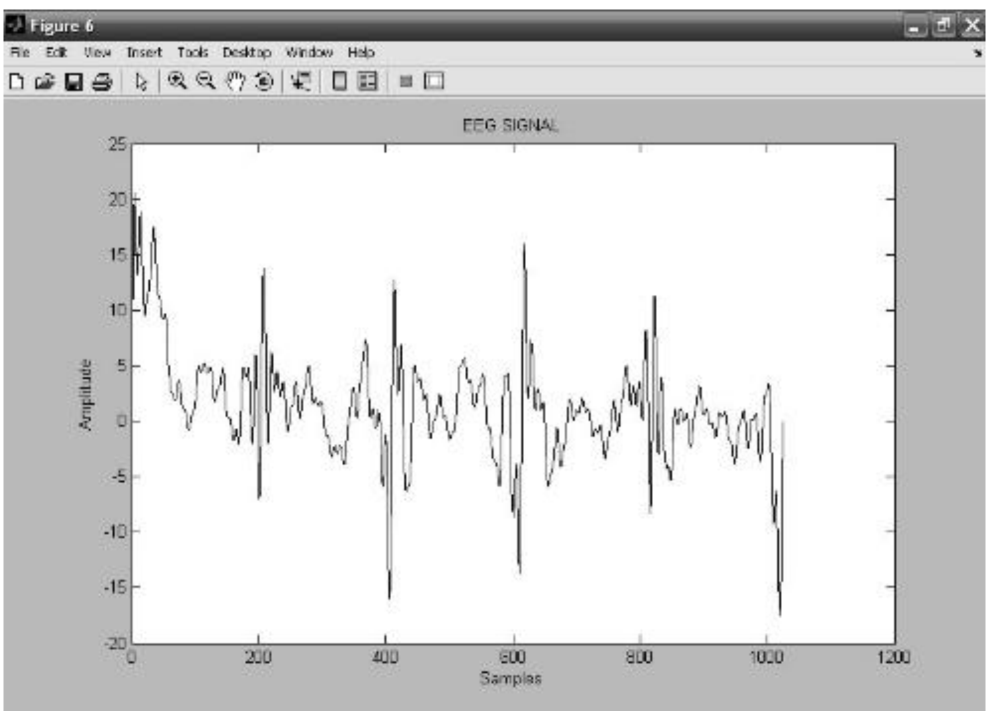


Figure 4
File Edit View Insert Tools Desktop Window Help
BETA WAVE
Amplitude
Samples
(d)



(e)



(f)

Figure 2 a. Delta_Wave b. Theta_Wave c. Alpha_Wave d. Beta_Wave e. Gamma_Wave f. Input EEG Signal

Table 1 Normal EEG brain waves

Ryhthm	Frequency (Hz)	Amplitude (uV)	Location & Recording
(α) Alpha_ Ryhthm	Eight-Thirteen	from Fifty to one hundred	Adults, resting with their eyes closed in the occipital area
(β) Beta_ Ryhthm	Fourteen-Thirty	Twenty	Frontal area, adult, mental activity
(θ) Theta_ Ryhthm	Five-Seven	Above Fifty	Emotional distress, children, drowsy adult
(δ) Delta_ Ryhthm	Two-Four	Above Fifty	Children in sleep

Research Objective

The goal of this system, consisting of a combination of hardware and software, is to diagnose the EEG. This is especially true for telemedicine, where Comp/Trans are critical. We propose a novel system architecture consisting of DWT and RLE to send a compressed ECG signal during acquisition to address this issue. This system is built on a compression-based data collection device that collects data in real time. To analyze the EEG signals, they're sent to a remote server after they've been acquired. To analyze the EEG signals, they're sent to a remote server after they've been acquired. As a result of lowering the data size and transmission time, EEG signal compression is critical in this case.

The basic aim of EEG signal compression is

1. Signal compression with appropriate size.
2. The most important clinical information should be preserved.
3. Minimize signal fidelity loss while increasing CR.

Lossy Compression

Lossy data compression decreases the number of bits in a file by evaluating and eliminating superfluous data. The most efficient data lossy compression technique is DWT, which should be picked out of all the options (Srinivasan and Ramasubba Reddy, 2010):

1. DWT is a powerful and influential method in the compression process, and methods based on DWT have been shown to perform well.
2. Have a little impact on the EEG signal data
3. Wavelet-based techniques offer strong compression performance and can compress EEG signal to multiple levels.
4. DWT is perfect for non- stationary signals compression.
5. Basically it gives multiple resolution decomposition of a signal
6. Signal sub-banding is easier and quicker utilizing DWT.

The Scenario of EEG Signals Compression

Compression Phase

1. Preprocessing of EEG Signals

The power line in the EEG signal sample has noise. To remove this noise, it is important to obtain the specific EEG feature. Each EEG signal is dissected utilizing the frequency response to generate the suitable pre-filter for the removal of signal noise. The sampling frequency of the chosen signals is 360 samples per second. As a result, the frequency response range was set to 0 Hz to 180 Hz utilizing Nikyst standards. The signals are noted in a frequency range of 0 to 50 Hz in the lower range and 130 to 180 Hz in the upper range. In a wider context. As a result, EEG signals can be pretreated with a notch filter with comparable ranges. These signals may be dormant if the original signals (OrgSig) have a high resolution. These actual (original) signals have a sampling frequency of 360, and the OrgSig is sampled by a factor of two. The normal EEG signal sample is shown in fig. (3) below.

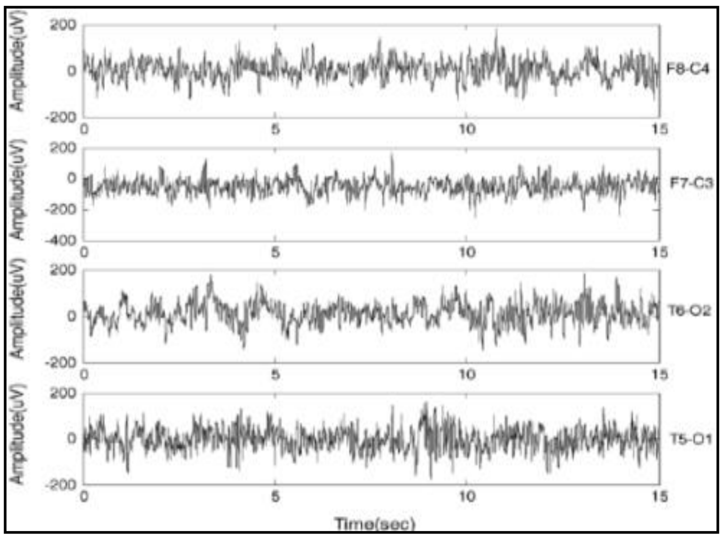


Figure 3 Normal EEG Signal Sample

The power line in the EEG signal sample has noise. To remove this noise, it is important to obtain the specific EEG feature. Each EEG signal is dissected utilizing the frequency response to generate the suitable pre-filter for the removal of signal noise. The sampling frequency of the chosen signals is 360 samples per second. As a result, the frequency response range was set to 0 Hz to 180 Hz utilizing Nikyst standards. The signals are shown in a frequency range of 0 to 50 Hz in the lower range and 130 to 180 Hz in the upper range. On a much grander scale. As a result, EEG signals can be pretreated with a notch filter with comparable ranges. These signals may be dormant if the OrgSig have a high resolution. These actual (original) signals have a sampling frequency of 360, therefore the OrgSig is sampled by a factor of two (Gunapriya and Sabrigiriraj, 2016) (Esquível and Krasii, 2021).

Peak Detection

During the peak detection procedure, the highest signal peaks are identified. The suggested peak identification method is based on the EEG signal's properties. The amplitude of the highest threshold is one of the EEG's properties. The amplitude of the threshold is the magnitude of the peak's smallest possibility. Values below this criterion are not considered maximum. The minimal distance between the vertices of the bottom portion is the second EEG property. The improved detection approach proposed here is discussed in detail. First, in certain instances, provide the maximum value. The peak is taken into account if the highest value exceeds the threshold. The maximum threshold amplitude may be exceeded in samples adjacent to the previously identified peak. As a result, all surrounding samples are eliminated from the current identified peaks in order to detect the following peak. This will eliminate the identification of pseudo-peak data around the freshly discovered peak (Bigdely-Shamlo et al., 2015).

Linear Transformation

Several shifts are utilized to analyze the EEG signal. A sample is taken between two consecutive peaks in each cycle. A distinct FFT is computed for each EEG shift. The FFT results are utilized to determine the storage goal. To investigate the influence of quantification, several quantification factors ranging from 0: 1 to 4 were utilized.

Entropic Coding (Hoffman Coding)

For entropy coding, Huffman coding is utilized. FFT can be anticipated because of the repetitive EEG output. Some of the FFT values have a high likelihood of occurring. After computing an FFT, each FFT result is compared to a histogram. The frequency graph depicts how often each of the FFT values occurs. As a result, each FFT sample value's probability may be determined. The majority of the FFT sample values were found to be in the -20 to +20 range. Other values are difficult to predict (Candan and Inan, 2014).

1. EEG Signals Reconstruction Phase

The reverse compression method is utilized during the reconstruction phase of EEG signals, also known as decompression. The encoded entropy signal, the inverse linear transformation, and post-processing are all included in this decoding step. The built-in EEG signal is designed to renew. The decompression mechanism receives the EEG signal as input (Abo-Zahhad, Abbas and Ahmed, 2015).

- **Decoding of the Entropic Encoded Signal**

In a compressed signal (ComSig), there are two sorts of bits. The Huffman decoder receives a message containing Huffman coding codes first. The Huffman Decoder uses the Huffman Dictionary to decode the bits. The second bitstream decoder, which lacks Huffman coding codes, follows. The DWT values and their indices in the original vector are contained in the values of the second bit sequence. The values of these indices are allocated to the Huffman block in the second bit stream, which was previously decoded with the aforementioned DWT values (Dauwels et al., 2013).

- **Reverse Linear Transformation**

In the compression step, DWT was utilized for the linear transformation. In the reverse procedure, the discrete transformation of discrete wavelets (IDWT) is employed. For each cycle, an IDWT is computed. Each rotation is based on a sample taken between two peaks. Based on peak indications, the reverse entropy coding result is split into many cycles. The data is then sent to the EFT block. Because of the quantization employed in the compression step, the output of the EEG signal will be rebuilt with a specific tolerance (Alharbi, 2018).

The IFFT signal is supplied to the samples during the postprocessing step. The sample output is then sent via a post-stop band filter. The EEG signal is reconstructed utilizing a synthetic signal. To estimate the performance of the recommended approach, this is compared to the original reference (Srinivasan, Dauwels and Reddy, 2013).

Materials and Methods

Overview

EEG (Electroencephalography) involved a recording of the electrical potential stimulated by the scalp.

The proposed method consists of two phases: compression phase and decompression phase as shown in figures (4). Compression phase show both the EEG signals compression that is utilized at transmitter side (the patients) via telemedicine, and decompression phase is the

EEG signals decompression at the receiver side (the specialists) via telemedicine (Abdulbaqi, A.S. and Mahdi, R.H., 2018).

To achieve the compression process, there are 50 EEG signals records related have been preprocessing before backward signal difference (BSD) is applied. The preprocessing begin with filtering the EEG signals to reduces the power line interference of 50 Hz, and then applied backward signal difference for EEG signals which lossless compresses by 50%. After that, applied DWT for EEG signals after applying and implement threshold and quantization grades of these signals(Zhu, 2010) (Dutta, 2015).

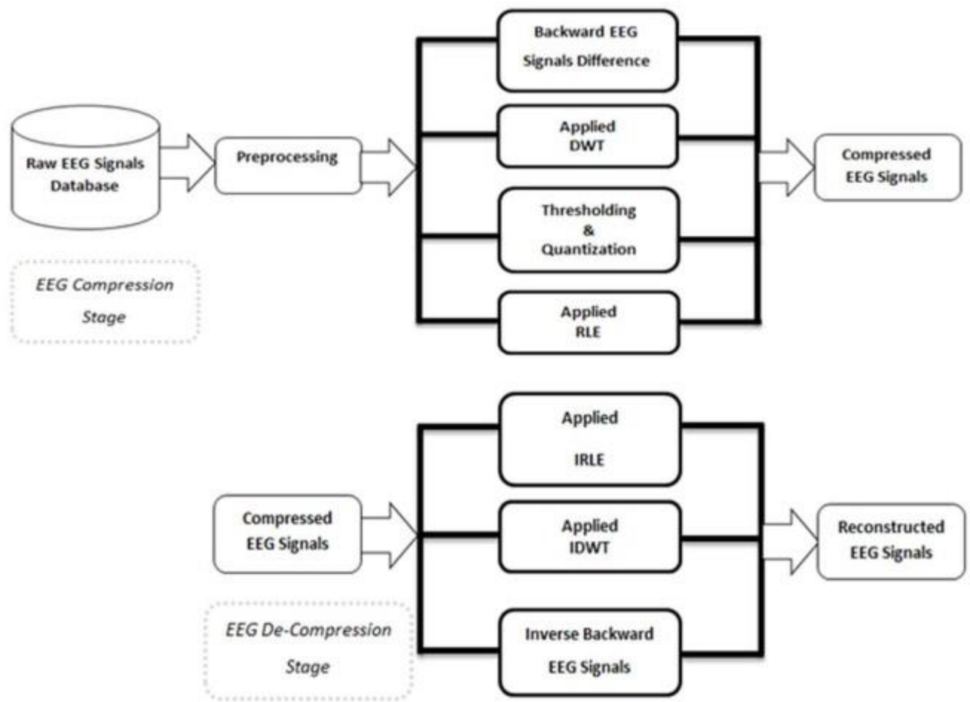


Figure 4 Two Stages of EEG Signals processing – Compression and Decompression (Reconstruction)

Savitzky–Golay Filter (SGF)

A digital filter (also called DSP filters (digital smoothing polynomial filters)), utilized for signals data smoothing to set of digital data points in order to improve SNR (signal-to-noise ratio) without signals data deforming. SG filter smoothing filters present a better standard averaging FIR filters, which results in the filtering of a large portion of the high-frequency digital signal content along with the noise. The SG filter is very effective conserve a high-frequency component of signals if this signals compared with finite impulse response (FIR) filters. In the figure (5) below demonstrate the original EEG signals with utilizing Savitzky –Golay filter (Artameeyanant, Sultornsanee and Chamnongthai, 2017).

In order to achieved moreover signals compression at the transmitter side, RLE is applied. At the reconstruction side, applied inverse run length encoding (IRLE) and inverse discrete wavelet transform (IDWT), and finally applied backward difference.

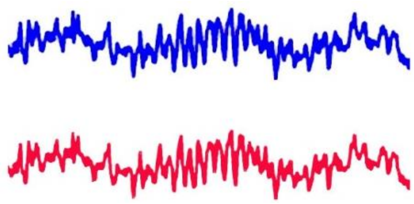


Figure 5 (a) The Noisy original EEG Signal and, (b) Enhanced EEG Signal after applied SG Filter

Compression with Wavelet Transform

The wavelet transformations analysis (WTA) of an EEG signal may be performed in both the time and frequency domains, and it preserves the signal's local characteristics extremely well. Then it is ideally suited for usage in biomedical signal compression, where it retains the EEG signal's safety characteristics (Kolekar and Sengupta, 2015).

In the time domain, a function of mother wavelet is ψ (t) with zero average, according the below equation (1):

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \qquad (1)$$

The function of daughter wavelet with parameter p (scale parameter) and parameter q (translation parameter) can be represented by the following equation (2):

$$\psi^{p,q}(t) = \frac{1}{\sqrt{p}}\psi\left(\frac{t-q}{p}\right) \qquad (2)$$

Wavelet transform can be calculated for a function x(t) by utilizing the cross-correlation of x(t) function of daughter wavelet ψp,q (t) according the below equation (3):

$$Xw\ (p,q)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi * (\frac{t-q}{p})\ dt \qquad (3)$$

According to the equation (3), the digital implementation for this equation is DWT.

Compression with RLE

Run length encoding (RLE) has been utilized to encode transform coefficients of EEG signal which is repeated in nature. DWT coefficients include a long run of data and can be collected as a single data value. RLE uses redundancy of data and it provides an improvement of compression ratio (CR) of EEG signal (Lambert, L. et al., 2015).

Performance Parameters

Both parameters, compression efficiency and error criteria, can be utilized to judge the success of an EEG compression technique. These characteristics include the compression method's capacity to reconstruct the EEG signal while preserving the essential data.

To test the quality of reconstruction signal, the following performance parameters are utilized:

1. Compression Ratio (CR)

The ratio of the OrgSig size to the ComSig size is known as CR. The CR indicates how much superfluous data is removed by the compression technique. The lower the CR, the fewer bits are required to store or transfer data, as shown in the equation below (4):

$$\mathrm{CR} = \frac{\text{The size of OrgSig in byte}}{\text{The size of RecSig in byte}} \quad (4)$$

If the CR is a high value, it means a high compression performance.

2. The Percentage Root Mean Square Difference (PRD)

PRD utilized to measures the error between the OrgSig and the RecSig and can be described as a following equation(5) (Sriraam, 2011):

$$\mathrm{PRDN} = \sqrt{\frac{\sum_0^{N-1}(X(n)-Y(n))^2}{\sum_0^{N-1}(X(n)-\mathrm{mean}\ (Xn)))^2}} \times 100\% \quad (5)$$

3. The Quality Score (QS)

QS can be described as a following equation(6):

$$\text{Quality Score (QS)} = \frac{\mathrm{CR}}{\mathrm{PRD}} \quad (6)$$

A high value of QS refer to a high quality of compression (Abo-Zahhad, Abdel-Hamid and Mohamed, 2014).

4. The Root Mean Square Error (RMS)

RMS provides a measure of the error in RecSig with respect to the OrgSig, and can be described as a following equation (7):

$$\mathrm{RMS} = \sqrt{\frac{\sum_0^{N-1}(X(n)-Y(n))^2}{N-1}} \quad (7)$$

5. The Signal to Noise Ratio (SNR)

SNR can be described as the following equation (8):

$$\mathrm{SNR} = 10 \times \log\left(\frac{\sum_0^{N-1}(X(n)-\mathrm{mean}(X(n)))^2}{\sum_0^{N-1}(X(n)-Y(n))^2}\right) \qquad (8)$$

The dataset of the EEG signals from the Florida university[28].

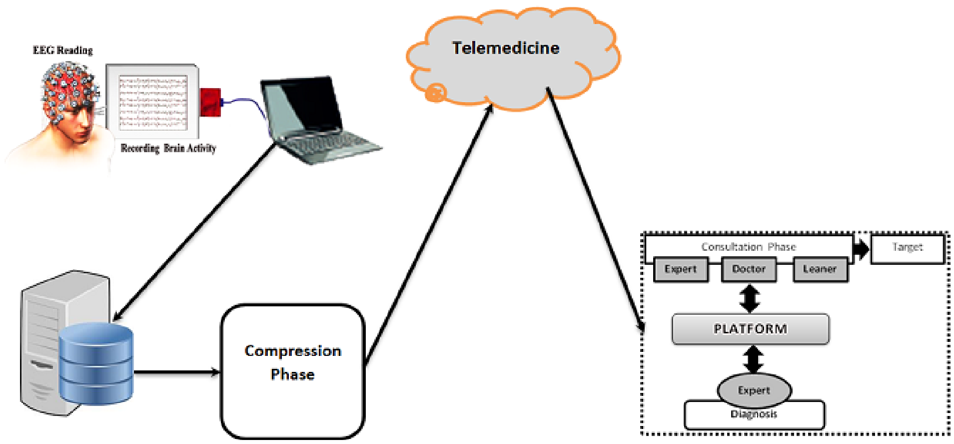


Figure 6 Overall System Structure

Results and Discussion

This section explains the performance evaluation of the proposed method for 20 patients records of EEG data taken from Florida university database. The results of the compression are shown in Table 1.

Table 2 Compression outcomes of the proposed method

Patient Rec. No.	PRD	PRDN	RMS	SNR	QS	CR
Rec.10	0.23	7.34	2.16	53.8	167	39.9
Rec.11	0.18	4.48	1.73	59.4	267	48.7
Rec.12	0.5	15.5	5.32	69.5	55.5	27.9
Rec.13	0.33	5.59	3.19	58.9	100	33.9
Rec.14	0.34	7.02	3.71	55.2	217	75
Rec.15	0.34	5.62	3.4	55.8	169	59
Rec.16	0.36	5.73	3.34	58	180	65.2
Rec.17	0.66	4.71	7.63	59.5	59.6	39.6
Rec.18	0.30	10.00	3.47	61.2	249	75.2
Rec.19	0.38	5.06	4.17	60.8	99.7	38.6
Rec.20	0.18	2.73	1.54	72	248	45
Rec.21	0.24	6.10	2.54	61.4	188	46.1
Rec.22	0.22	5.12	1.9	60.7	244	53.9
Rec.23	0.32	4.06	3.18	62.6	149	48.3
Rec.24	0.21	9.51	2.04	64.3	201	42.9
Rec.25	0.28	4.30	2.59	61.8	164	46.8
Rec.26	0.50	3.75	4.15	62.7	76.9	38.7
Rec.27	0.31	6.40	2.78	61.4	148	47
Rec.28	0.67	7.1	5.71	51.2	63.6	42.6
Rec.29	0.47	3.42	3.95	63.4	81.8	38.5

The original EEG signal and Rec-EEG signal, and the error signal for the record no. 10 are shown in Fig. 6 and it is clear that Rec-EEG signal retains the characteristic features of the original EEG signal very well.

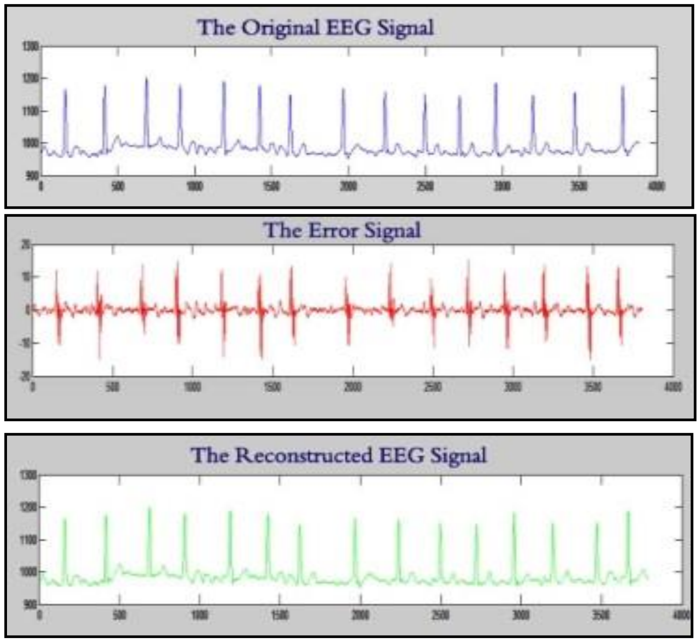


Figure 7 Three samples implementation of the record 10

Based on the outcomes shown in table 2, it's clear that the performance of the proposed method provides a better compression than the other algorithms as shown in the records no. 10, 27 and 29 has been shown in Table 3.

Table 3 Comparison between the Compression Results

Method	CR	PRD
Darius Birvinskas et al. (2015)	2.66	10.33
Hakan G¨urkan et al (2009)	14.4	8.01
S.Chitra et al.(2015)	1.8347	0.0802
Seema. A. Taywade et al. (2012)	21.30	1.75
The proposed method	39.9	0.23

Fig. 7, refer to the CR and PRD values plots for 10 - 21 records of EEG signal. From these plots, it can be seen that there are not important variation in CR and PRD values. It means that the proposed algorithm is proper for Comp/Trans of various morphologies of EEG data.

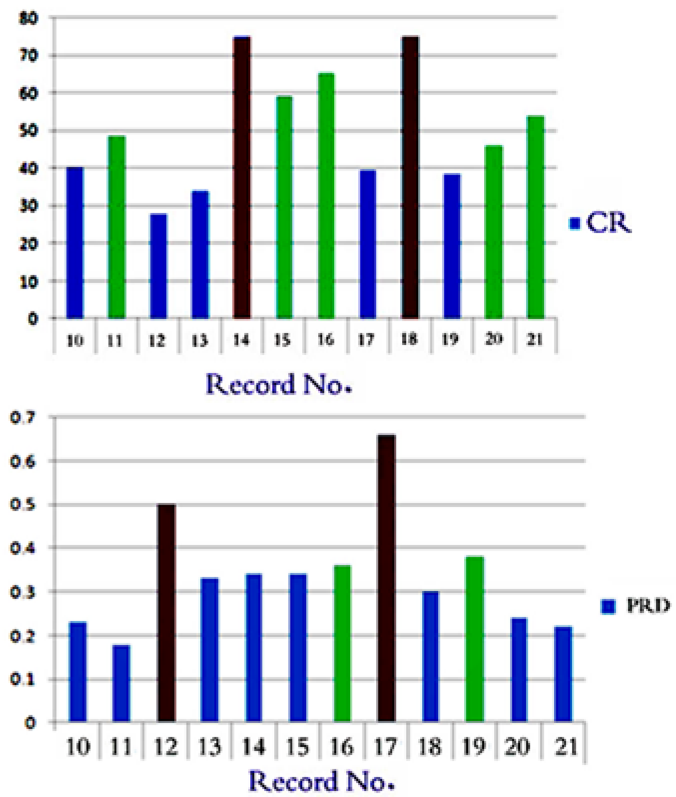


Fig. 7 Parameters of CR and PRD plotted from 10 – 21

The below fig. (8), show the input EEG signals and extracted the EEG output signals with different types of EEG signals:

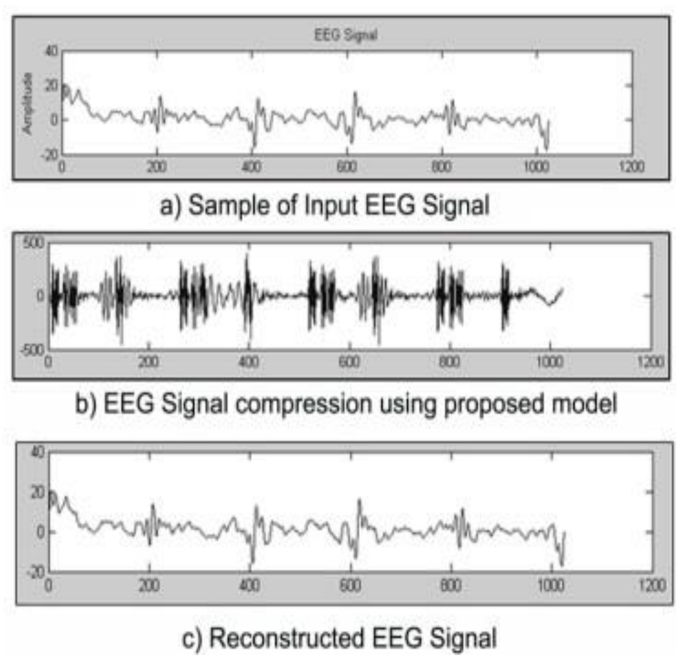


Figure 8 Samples of input, Compressed, and Rec-EEG signal

Conclusion

Although storage capacity and transmission speed have greatly improved, EEG data compression remains a key challenge in today's communication systems. Since their diagnostic characteristics establish a common attempt to all compression elements (efficient EEG data transfer and compression) while leaving diagnostic features unchanged, this is the reason. It was attempted to enhance detecting algorithms but it was not successful. CR, bandwidth, SNR, QS, data dependability and quality of service, as well as security and privacy, need to be improved in order to face the real-time challenge of Comp/Trans of EEG data in real-time. DWT and RLE were utilized to create a hybrid Comp/Trans system that is both efficient and effective.

References

Lee, S., Kim, J., & Lee, M. (2011). A real-time ECG data compression and transmission algorithm for an e-health device. *IEEE Transactions on Biomedical Engineering, 58*(9), 2448-2455.

Sriraam, N., & Eswaran, C. (2008). Performance evaluation of neural network and linear predictors for near-lossless compression of EEG signals. *IEEE Transactions on Information Technology in Biomedicine, 12*(1), 87-93.

Sriraam, N. (2011). Quality-on-demand compression of EEG signals for telemedicine applications using neural network predictors. *International journal of telemedicine and applications*, 1–13.

Pai, Y.T., Cheng, F.C., Lu, S.P., & Ruan, S.J. (2012). Sub-trees modification of Huffman coding for stuffing bits reduction and efficient NRZI data transmission. *IEEE transactions on broadcasting, 58*(2), 221-227.

Tao Ma, Shrestha, P.L., Hempel, M., Dongming Peng, Sharif, H., & Hsiao-Hwa Chen (2012). Assurance of Energy Efficiency and Data Security for ECG Transmission in BASNs. *IEEE Transactions on Biomedical Engineering*, *59*(4), 1041–1048.

Ma, T., Shrestha, P.L., Hempel, M., Peng, D., Sharif, H., & Chen, H.H. (2012). Assurance of energy efficiency and data security for ECG transmission in BASNs. *IEEE Transactions on Biomedical Engineering, 59*(4), 1041-1048.

Ke-Jing, H.E. (2010). High Performance Lossless Compression of Scientific Floating Data. *Chinese Journal of Computers, 33*(6), 966–976.

Zhang, Z., Jung, T.P., Makeig, S., & Rao, B.D. (2012). Compressed sensing of EEG for wireless telemonitoring with low energy consumption and inexpensive hardware. *IEEE Transactions on Biomedical Engineering, 60*(1), 221-224.

Kumar, B.B.S., & Satyanarayana, P.S. (2020). Correlative Analysis of EZW and SPIHT Compression Algorithms using Sevenlets Wavelet Technique. (2020). *International Journal of Innovative Technology and Exploring Engineering*, *9*(5), 1099–1104.

Abdulai Sawaneh, I. (2018). An Effective Method for e-Medical Data Compression Using Wavelet Analysis. *International Journal of Medical Imaging*, *6*(3), 25.

Guy Lysmos, M.E., & Hanoune, M. (2020). Hybrid Data Compression System in Smart E-Health Gateway for Medical Monitoring Applications. *International Journal of Computer Science and Engineering, 7*(1), 1–6.

Hanoune, M., & Lysmos, M.E.A.G. (2020). Data Compression mechanisms in an intelligent E-Health gateway for medical monitoring applications. *Procedia Computer Science, 175,* 578-584.

Amin, H.U., Yusoff, M.Z., & Ahmad, R.F. (2020). A novel approach based on wavelet analysis and arithmetic coding for automated detection and diagnosis of epileptic seizure in EEG signals using machine learning techniques. *Biomedical Signal Processing and Control, 56*.

Srinivasan, K., & Reddy, M.R. (2010). Efficient preprocessing technique for real-time lossless EEG compression. *Electronics Letters, 46*(1), 26-27.

Gunapriya, B., & Sabrigiriraj, M. (2017). Real-time implementation and performance evaluation of brain emotional learning developed for FPGA-based PMBLDC motor drives. *Journal of Testing and Evaluation, 45*(3), 987-1004.

Esquível, M.L., & Krasii, N.P. (2021). A wavelet-based neural network scheme for supervised and unsupervised learning. *Neural Computing and Applications,* 1-16.

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K.M., & Robbins, K.A. (2015). The PREP pipeline: standardized preprocessing for large-scale EEG analysis. *Frontiers in neuroinformatics, 9,* 16. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4471356/

Candan, Ç., & Inan, H. (2014). A unified framework for derivation and implementation of Savitzky–Golay filters. *Signal Processing, 104,* 203-211.

Abo-Zahhad, M., Ahmed, S.M., & Abbas, S.N. (2015). State-of-the-art methods and future perspectives for personal recognition based on electroencephalogram signals. *IET Biometrics, 4*(3), 179-190.

Dauwels, J., Srinivasan, K., Reddy, M.R., & Cichocki, A. (2012). Near-lossless multichannel EEG compression based on matrix and tensor decompositions. *IEEE journal of biomedical and health informatics, 17*(3), 708-714.

Alharbi, N. (2018). A novel approach for noise removal and distinction of EEG recordings. *Biomedical signal processing and control, 39,* 23-33.

Srinivasan, K., Dauwels, J., & Reddy, M.R. (2012). Multichannel EEG compression: Wavelet-based image and volumetric coding approach. *IEEE journal of biomedical and health informatics, 17*(1), 113-120.

Abdulbaqi, A.S., & Mahdi, R.H. (2018). Biometrics detection and recognition based-on geometrical features extraction. *In International Conference on Advance of Sustainable Engineering and its Application (ICASEA),* 59-63.

Zhu, Z.Y. (2010). A novel image fusion approach based on rough set and wavelet analysis. *In Key Engineering Materials, 439,* 1069-1074.

Dutta, T. (2015). Medical Data Compression and Transmission in Wireless Ad Hoc Networks. *IEEE Sensors Journal, 15*(2), 778–786.

Artameeyanant, P., Sultornsanee, S., & Chamnongthai, K. (2017). Electroencephalography-based feature extraction using complex network for automated epileptic seizure detection. *Expert Systems, 34*(3).

Kumar, R., Verma, A.R., Gupta, B., & Kumar, S. (2021). Dual-tree sparse decomposition of DWT filters for ECG signal compression and HRV analysis. *Augmented Human Research*, *6*(1), 1-7.

Kolekar, M.H., & Sengupta, S. (2015). Bayesian network-based customized highlight generation for broadcast soccer videos. *IEEE Transactions on Broadcasting*, *61*(2), 195-209.

Lambert, L., Dhif, I., Ibraheem, M.S., Granado, B., Hachicha, K., Pinna, A., Garda, P., Kubis, N., Kaddouh, F., Heudes, D., & Terosiet, M. (2015). Smart-EEG: a Tele-medicine System for EEG Exams. *In JETSAN 2015*.

Sriraam, N. (2011). Quality-on-demand compression of EEG signals for telemedicine applications using neural network predictors. *International journal of telemedicine and applications*, 1-13.

Abo-Zahhad, M.M., Abdel-Hamid, T.K., & Mohamed, A.M. (2014). Compression of ECG signals based on DWT and exploiting the correlation between ECG signal samples. *International Journal of Communications, Network and System Sciences*, *7*(1), 53–70.

Noruzi, A. (2016). ArXiv popularity from a citation analysis point of view. *Webology*, *13*(2), 1-7.