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Design and Implementation of a Telehealthcare Interactive System for Cerebral Disorders Detection Based on Virtual Instruments and EEG Signals

Israa Badr Al-Mashhadani

Department of Computer Engineering, College of Engineering, Al-Nahrain University, Baghdad 10072, Iraq

Corresponding Author Email: israa.b.al-mashhadani@nahrainuniv.edu.iq

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ABSTRACT

The proposed method deals with the study and analysis of EEG signal using LabVIEW Biomedical toolkit effectively. The objective of this paper is to identify brain disorders, using LabVIEW. An analysis of cerebral disorders was conducted using LabVIEW. A technique is suggested that uses LabVIEW Biomedical for analyzing EEG signals. Devices considered in this study include signal acquisition, data interfaces such as myDAQ, amplification, and feature extraction capabilities. Signal conditioning is adopted with an undertaking amplifier (LM741), followed by an instrumentation amplifier (AD8232). DAQ cards are ADC cards. A biomedical toolkit is used to extract the features of the EEG signal using LabVIEW. Based on the extracted features, a comparison is conducted between the patient's code defaults and the number of arrhythmic features found. Following this, specialists can monitor their patients' EEG signals remotely and dynamically in real-time via a web page without installing any software from a telemedicine application. This system will bridge the gap between the patient's deteriorating health condition and healthcare entities.

1. INTRODUCTION

The Brain-Computer Interface (BCI) is not dependent on peripheral nerves or muscles. EEG signals are being used to detect consciousness in a brand new method of communication and control. BCI systems are generally composed of three components: acquiring EEG signals, processing data, and incorporating peripherals. As part of data processing, features are extracted, classified, and preprocessed. EEG signals must be preprocessed in order to remove noise before being used for BCI. The purpose of the present study is to preprocess EEG signals using LabVIEW for filtering and denoising in order to facilitate programming with the BCI Competition 2005 dataset and provide a good foundation for the implementation of a BCI system [1, 2].

In today's world, techniques like VB and VC are commonly used to develop software, which can pose a problem for BCI designers who don't have much experience with software development. NI's LabVIEW solution solves this problem. LabVIEW stands for Laboratory Virtual Instrument Engineering Workbench, which is a platform for visual system design and development [3]. Code compiling is minimal since it uses G for graphical programming. Block diagrams and virtual front panels are used instead to build virtual instruments. Developers are able to spend less time and effort on programming thanks to the G language. For data acquisition and instrument control, LabVIEW has become a standard tool in industry, academia, and research laboratories [4, 5].

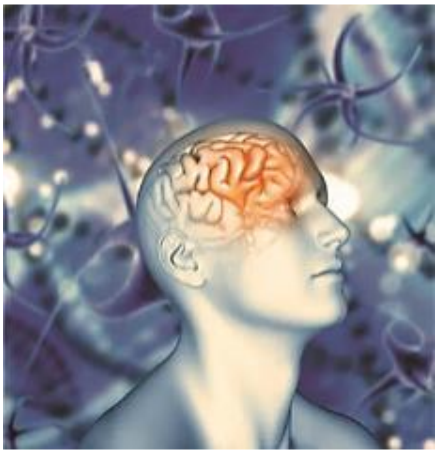


Figure 1. Brain disorder [3]

The brain controls all of the body's parts. Electrical activity in the brain is represented graphically by the EEG. In Figure 1, we can see an example of a normal EEG waveform. The EEG can be used to diagnose a wide range of brain diseases and conditions, including:

Epilepsy: Seizures are a tendency of epilepsy. A brain electrical storm induces convulsions and affects consciousness (uncontrolled movements). Some seizures produce cloudy consciousness or uncontrolled movement.

Infections: Germs may infect your brain or its coverings. Infected membranes cause meningitis. Headaches, disorientation, and stiff neck are common. Sometimes a spinal tap is needed to determine the infection's cause and provide the proper medications [6].

Mental illness: Mental, behavioral, and emotional issues may impair a person's functioning.

Disorders of the neurodegenerative brain: Neurodegenerative diseases are caused by faulty brain proteins. Alzheimer's, Parkinson's, and ALS are examples. They're usually slow-progressing and affect cognition, memory, or mobility. Most elderly have them. Some are genetic [7].

Neurodevelopmental disorders: Pediatric neurologists treat neurodevelopmental problems, which influence brain growth. Hereditary conditions may be evaluated by medical geneticists. If so, family therapy is provided.

Stroke: Strokes occur when a blood artery that feeds your brain becomes clogged or breaks. Both are sudden. Stroke harms brain tissue. This may affect speech, comprehension, vision, strength, feeling, and coordination. Strokes may cause dementia if enough brain tissue is destroyed. Strokes may cause seizures [6, 8].

Injuries of the traumatic brain: Gunshot wounds are among the traumatic brain injuries. A person's brain can be damaged when he falls, is involved in a car accident, is injured during a sports game, or is abused by a family member. Repeated head trauma (CTE) may lead to chronic traumatic encephalopathy. Neurosurgeons can treat piercings and bleeding. Psychologists, psychiatrists, and speech therapists can help with behavior and thinking following brain injury. Neurologists also treat injuries [5, 9].

Tumors: There is a possibility that brain tumors are caused by lung, breast, or colon cancer. Brain tissue or coverings can be affected by them. It is benign if a brain tumor develops slowly and does not spread to surrounding brain tissue. Infiltrating brain tissue is one of the first symptoms of malignant tumors [9].

For signal processing of EEG signals, LabVIEW software is used along with the biomedical toolkit for removing EEG features. LabVIEW (Laboratory Virtual Instrument Engineering Workbench) is used to create a virtual programming language. With LabVIEW, signals can be processed, acquired, and transmitted [10].

In recent decades, remote healthcare has become more popular. Due to its huge potential and potential applications, telemedicine has gained a lot of attention. Telemedicine systems have been implemented more frequently as a result. Data from this system is generally sent to the central system by this system. Data is processed by the central system to detect diseases (if any). Some systems also provide real-time monitoring. Datasets from different patients have to be processed by healthcare systems and reports are provided to patients over a long period of time. Monitoring the patient in real-time requires a physician on the other side of the system. A patient suffering from a brain disorder may suffer more when this scenario is not detected early. Detecting diseases within the system itself may be the solution to the above problem [11, 12].

2. WORK OBJECTIVES

The objectives of the work are:

(1) Preventing nervous stress from manifesting physically by detecting it in advance;

(2) Classify the signals according to their frequency;

(3) Alert the user when epilepsy is about to occur using a threshold;

(4) LabVIEW recruitment to identify heart disorders.

3. SYSTEM DESIGN

The components of the system (Figure 2) include:

Modules for sensors: An EEG signal is acquired from the patient using the sensor. We acquired the EEG signal from the patient using the AD8232 EEG sensor module [13].

NI myDAQ: This device provides the interface between the sensor module and the output device (laptop).

LabVIEW EEG signal processing: The acquired raw EEG signals are processed using LPF, HPF, and BPF to remove baseline wandering and noise [13].

Biological workbench: Biomedical images and biosensors can be acquired, preprocessed, extracted, and analyzed using these applications [14].

Communicate and transmit via the web: LabVIEW includes a G-Web-Server as part of its application software. Data can be sent to a database or a central system via the G-Web-Server. A real-time doctor-patient communication interface can be provided in situations requiring emergency steps [15, 16].

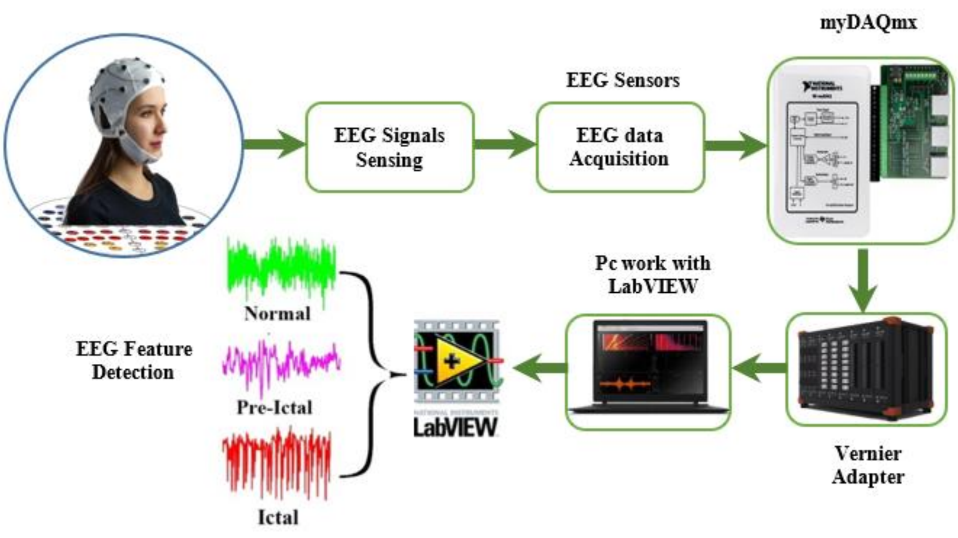


Figure 2. Proposed system design

4. SYSTEM METHODOLOGY

4.1 EEG signal acquisition

With the help of NI Multichannel DAQ devices, raw EEG signals can be acquired from EEG sensors using a variety of techniques. There is not a lot of bandwidth available in EEG. Raw EEG signals can be acquired using a variety of techniques. An EEG signal can be stored in the NI TDMS format for offline analysis. For example, the MIT-BIH database provides a variety of typical EEG signals. EEG data from MIT-BIH can be imported directly into the Biomedical Toolkit or Biomedical Workbench.

4.2 Extraction of features from EEG signals

Diagnoses are made by analyzing preprocessed EEG data for diagnostic features. There are several time-frequency characteristics included in the time-frequency domain, including Peak-Peak Means, Mean Squares, Variances, Hjorth Parameters: Activity, Mobility, Complexity, Maximum Power Spectral Frequency, Maximum Power Spectral Density, and Power Sum [17, 18]. Aside from approximate entropy and complexity, there are countless other properties of non-linear dynamical systems to take note of, such as Kolmogorov entropy, Lyapunov exponent, permutation entropy, singular entropy, Shannon entropy, and spectral entropy. Another feature that can provide useful information regarding abnormalities is tissue condition, in addition to sampling rate and conduction velocity. Using tests such as these, it is possible to detect brain diseases. As a result, the EEG signal-processing community has been paying close attention to it. With the Lab VIEW Biomedical Toolkit, EEG feature extraction is facilitated with an extractor VI and an application as shown in Figure 3 [15, 19].

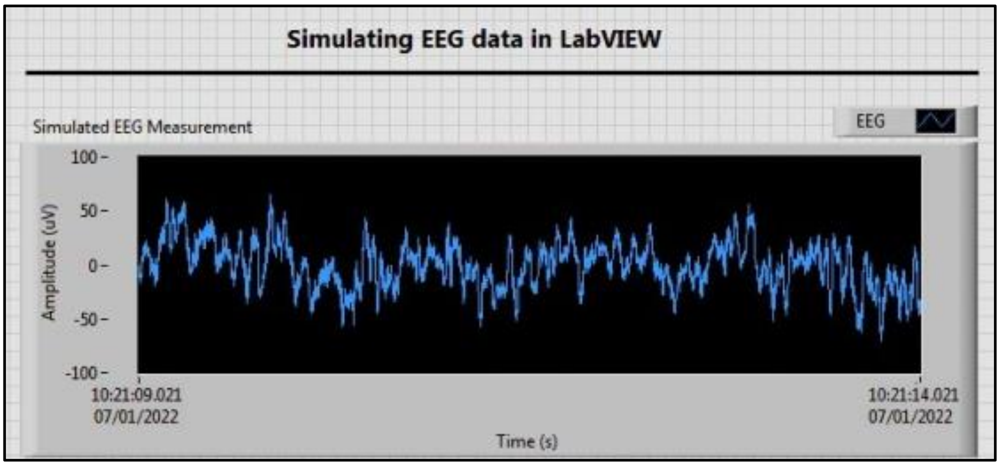


Figure 3. Feature extraction from EEG signal

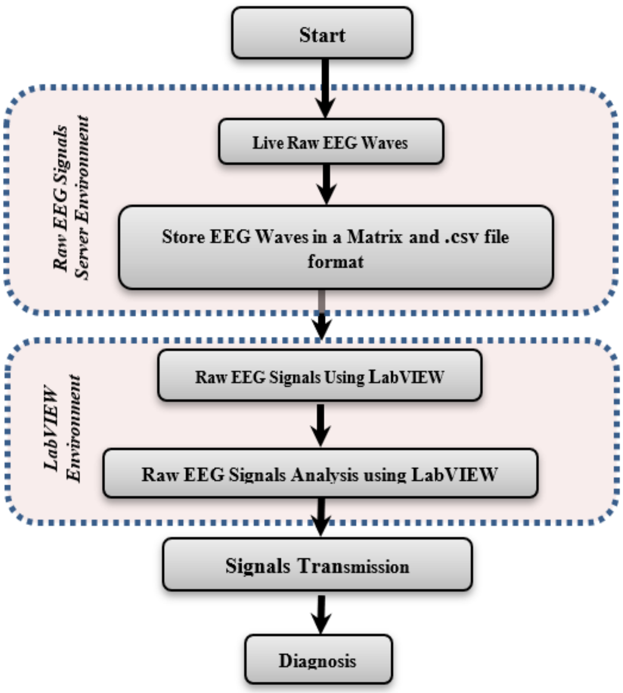


Figure 4. The proposed system flowchart

The Figure 4 describes the proposed system architecture.

To extract additional features from a signal, a feature extractor first detects a sample of the signal. EEG wave detection must therefore be accurate [4]. As shown in Figure 3, EEG signals are easily detectable. EEGs cannot be detected in certain brain diseases due to abnormal morphology [20, 21]. Before a feature can be extracted, the signal may need to be enhanced (preprocessed). Preprocessed signals are used to detect the position of each wave in the EEG signal. Since the signal enhancement may have altered all other features, you will extract them based on the original signal.

Using the EEG Feature Extractor in Lab VIEW Biomedical Toolkit, wave intervals can be directly synchronized with an EEG analyzer. Its application software uses G-Web_Server for its transmission unit. Recorded data can be sent to a central database or system via the G-Wen-Server [22]. In emergencies, doctors and patients can communicate in real-time using this module. Analyzing the wave interval signal after analyzing its features can help determine the health of the brain and nervous system [23].

In order to extract EEG features, we need to follow four steps:

1. EEG signals are acquired from DAQ or from files.
2. Preprocessing and filtering of EEG signals.
3. EEG feature extraction.
4. Perform an analysis of the extraction results.
5. Internet-based communication and transmission [18, 23].

Table 1 shows the normal EEG signals.

Table 1. The frequency band of normal EEG signals

Rhythm	The Frequency Band (Hz)	Behavior Trait
(α) Alpha_Rythm	8-13	Eyes Closed, Awake, Relaxed
(β) Beta_Rythm	13-30	Eyes Closed, Active Thinking, Alert
(θ) Theta_Rythm	4-8	Deep Mediation / Drowsiness, Light Sleep
(δ) Delta_Rythm	0.3-4	Deep Sleep
(γ) Gamma	30 and more	Hyperactivity / Unifying Consciousness

Table 2. Abnormal EEG parameters

EEG Wave	The Frequency of the EEG (in Hz)	Lower/Higher EEG Limits	Frequency (in Hz) of Average Obtained Frequency
Waves of Delta	4	0.5Hz / 3.99Hz	9.31
Wave of Theta	In the range of 4 to 7	It runs at 4.0Hz and 6.99Hz	13.61
Wave of Alpha	In the range of 7 to 14	It runs at 7.0Hz and 13.99Hz	20.41
Wave of Beta	In the range of 15 to 30	It runs at 15.0Hz and 29.99Hz	40.71
Wave of Gamma	In the range of 30 to 100	It runs at 30.0Hz and 99.99Hz	112.61

4.3 Detection of brain abnormalities

There are a number of atypical features that may exist in the functioning, structure, or biochemistry of the brain, referred to as brain abnormalities. Among the etiologies of abnormalities are genetic conditions, prenatal compressions, developmental disorders, traumatic conditions, toxins, and maternal or paternal diseases [11, 24].

Brain abnormalities are usually detected with diagnostic tools and imaging techniques. A proper diagnosis of brain abnormalities depends on the specific symptoms and suspected condition, which may require multiple tests. If you suspect you have brain health problems, a healthcare professional is your best resource. The EEG signal abnormalities shown in Table 2 [5, 25].

4.4 The myDAQ and LabVIEW systems

In LabVIEW, icons are used to visually represent applications. Dataflow determines how commands are executed. LabVIEW offers wizards for configuring DAQ devices, as well as tools for building applications and configuring computer-based instruments [26, 27]. A LabVIEW user interface is created using tools and objects. A front panel displays the user interface. Functions are controlled by graphical representations of objects on the front panel. A flow chart and a block diagram share some similarities. When the program is running, the user interacts with the front panel. The program can be edited, data can be shown in real-time, and the user can control it as well. Each of the front panel indicators and controls has a terminal. By wires, control blocks can be connected to functions on the block diagram, and results can be transferred to other functions as well. A PC-connected acquisition device is used for this work. By exchanging inputs with the control element, the control element generates outputs. A PC is connected to a data acquisition device to implement control algorithms. A control signal is issued to the final element after the process has been completed, using software such as LabVIEW. Set points are compared to process values in order to determine if the control signal is appropriate. As well as converting analog signals into digital signals, the DAQ device can also convert digital signals into analog signals. This project relies on an NI myDAQ card (Figure 5) [9, 28].

The materials required to complete this article include two Male-Male Breadboard Wires, a 220-ohm Resistor, a mySTEMTM Project Board, and a National Instruments myDAQ [17].

myDAQ device is a low-cost portable data acquisition device that uses NI LabVIEW software instruments for capturing, analyzing, and recording real-world signals. For electronics exploration and sensor measurements, NI myDAQ is the ideal tool. Combining NI LabVIEW with a PC allows us to analyze and process acquired signals anywhere, anytime. An analog or digital signal can be generated or acquired using this device in LabVIEW [24, 29, 30] (Figure 6).

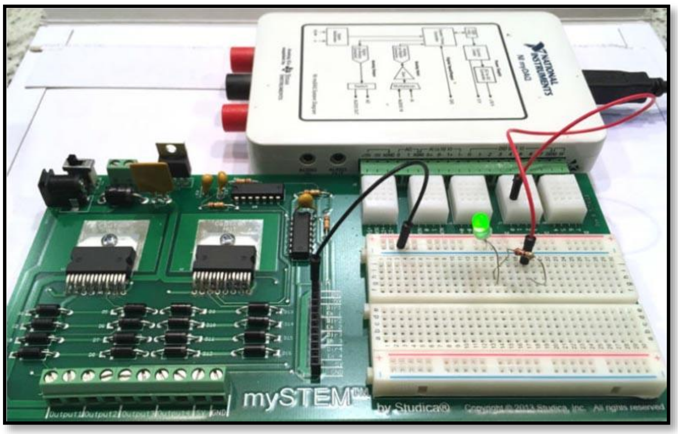


Figure 5. NI my DAQ

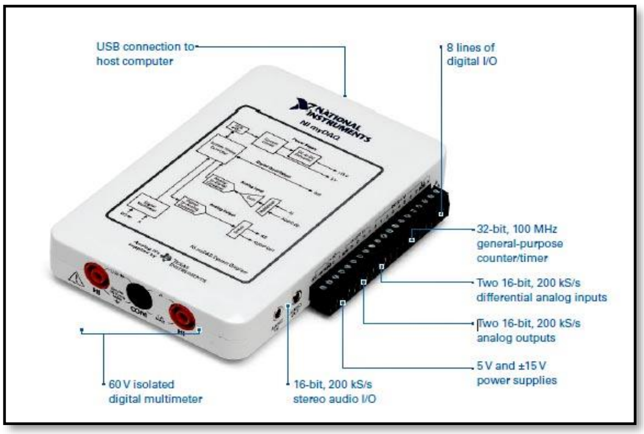


Figure 6. Connector I/O for NI myDAQ 20-position screw terminals

5. RESULTS AND DISCUSSION

Data transmission was also tested successfully with a remote transmission module to ensure real-time communication between Tier 1 (Specialists) and Tier 2 (Patients). As shown in Figure 7, the remote monitoring system is operated from a remote location. The extracted EEG parameters are then compared to the normal EEG parameters.

An abnormality in the current EEG will be indicated by any mismatch. According to Figure 8, the enlisted disease waveforms illustrating the proposed system's detection technique are listed.

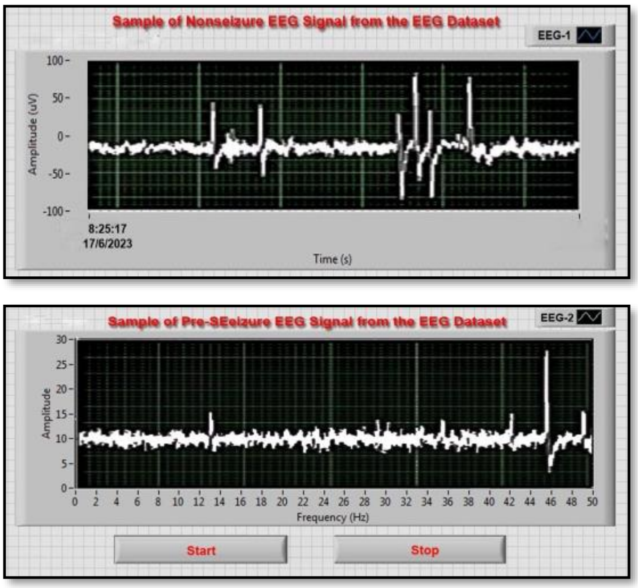


Figure 7. Normal EEG signal and its components analysis

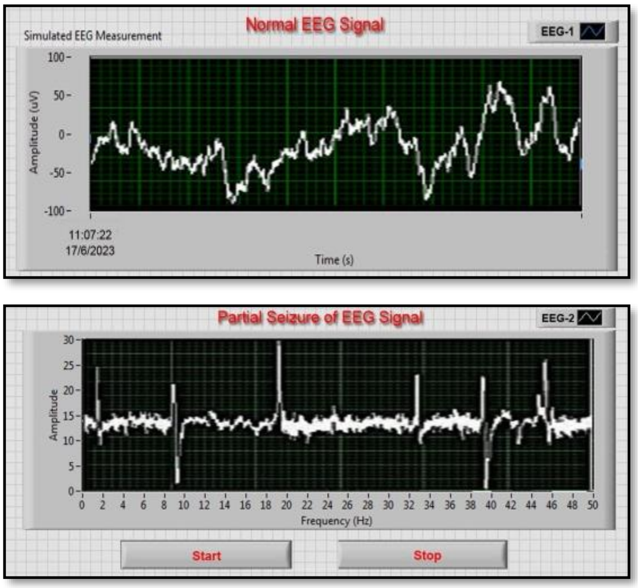


Figure 8. Sample of (non-seizure) and (pre-seizure) EEG signal from the EEG dataset

A biomedical toolkit can easily simulate EEG signals in Lab VIEW. It is always necessary to analyze the signal in order to determine what state the human is in. With the help of EEG, the signals are simulated.

Using the file source (.edf) obtained, the input is provided. Based on the set threshold, the following results were obtained:

Case 1: An ordinary person (Normal):

Table 3 shows the average wave values obtained by averaging the EEG signals from five different normal individuals. Normal person's EEG signals are used to plot an average frequency graph.

Table 3. A features vector for human cases

Direction/EEG Bands	Forward	Backward	Left	Right	Neutral
A band called Delta	0.9432	0.9386	0.925	0.9357	0.9169
A band called Theta	0.0456	0.0466	0.053	0.05	0.0603
A band called Alpha	0.0312	0.0334	0.0351	0.0328	0.0354
A band called Beta	0.0199	0.0214	0.027	0.0215	0.0274

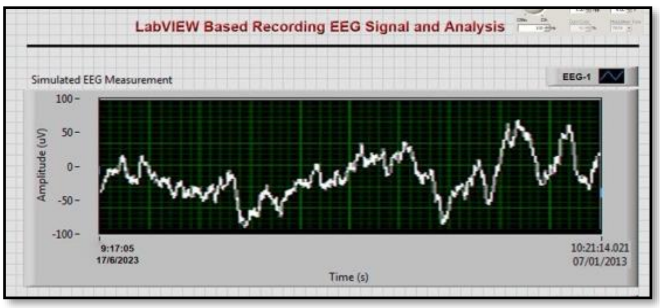
Case 2: An extraordinary person (Abnormal):

A patient with a nervous attack (epilepsy) is sampled for the ".edf" file by obtaining the (.edf) file of the patient. The file is provided to LabVIEW for building the simulation model. Table 4 shows the frequency distribution of epileptic EEG signals. The performance measurement variables are described for the EEGs signals include CR, PRD, PRDN, QS, and SNR in Table 4.

Table 4. Performance measurement variables for EEG signal compression and reconstruction

EEG Signals Records	CR	PRD	PRDN	QS	SNR
EEG Rec #101	15.96	3.33	1.72	7.82	51.03
EEG Rec #102	13.02	3.53	1.44	7.84	51.93
EEG Rec #105	17.01	2.03	1.24	14.03	89.92
EEG Rec #107	9.94	2.43	1.91	10.13	64.13
EEG Rec #109	12.01	3.13	2.93	5.93	64.03
EEG Rec #113	16	2.54	2.55	10.03	62.95
EEG Rec #115	11.33	2.73	1.43	8.93	64.22
EEG Rec #117	11.93	2.93	1.93	7.04	82.27
EEG Rec #118	7.8	2.23	1.53	10.53	69.94
EEG Rec #122	14.94	2.26	2.95	8.94	73.65
EEG Rec #123	15.58	2.23	1.79	7.12	63.78
EEG Rec #125	13.93	5.33	5.02	4.35	52.21
Total Average of Values	13.2875	2.8916	2.203	8.5575	658383

A frequency can be calculated from a seizure patient's EEG signal in Figure 9. The area above the threshold represents epileptic seizure occurrence amplitude values, which are much higher than normal seizure occurrence amplitude values. Following analysis of EEG power spectrum ratios.



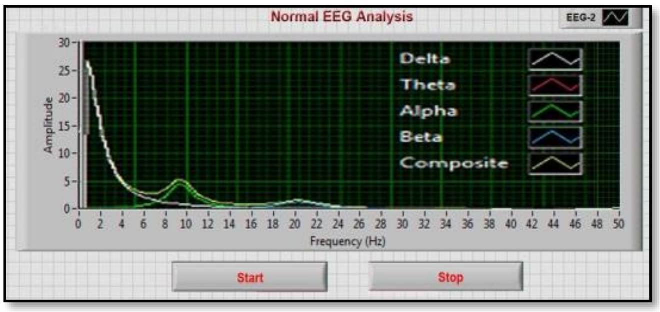


Figure 9. Sample of (normal) and (partial seizure) EEG signal from the EEG dataset

One of the most challenging aspects of EEG compression and reconstruction is determining the error criterion which measures the ability of the signals to maintain the appropriate data after they have been reconstructed. Various objective error measurements, such as SNR and PRD, are used to calculate reconstruction mistakes. On the other hand, the reconstructed EEG should have (High CR, High QS, and Low PRD) features to be an acceptable readable signal by a specialist physician.

6. SYSTEM PERFORMANCE MEASUREMENT

6.1 Compression ratio

Compression ratio (CR) can be described as a ration between no. of bits and compressed signals.

$$CR(\%) = \frac{File\ Bits\ Size\ Uncompressed}{File\ Bits\ Size\ Compressed} \tag{1}$$

6.2 Percent of root-mean-square difference

EEG compression algorithms typically use percentage root mean-square differences percent of root-mean-square difference (PRD) as follows:

$$\mathrm{PRD}(\%) = \sqrt{\frac{\sum_{n=1}^{N}(x(n) - x'(n))^2}{\sum_{n=1}^{N} x^2(n)}} \times 100 \tag{2}$$

6.3 Percent RMS difference normalised

This formula can be used to define percent RMS difference normalised (PRDN).

$$\mathrm{PRDN}(\%) = \sqrt{\frac{\sum_{n=1}^{N}[x(n) - x'(n)]^2}{\sum_{n=1}^{N}[x(n) - avg(x(n))]^2}} \times 100 \tag{3}$$

6.4 Quality score (QS)

Here is the CR to PRDN ration:

$$\mathrm{QS} = \mathrm{CR} \,/\, \mathrm{PRDN} \tag{4}$$

6.5 Signal to-noise-ratio (SNR)

The format of SNR as a following:

$$PRDN(\%) = \frac{10\log\sum_{0}^{N-1}(x(n) - mean\ (x))^2}{\sum_{0}^{N-1}(x(n) - y(n))^2} \tag{5}$$

A reconstructed EEG signal is shown as y, where x represents the original signal.

7. CONCLUSION

This paper presents an automated EEG signal-analyzing system that is fast and effective. There is flexibility in the system. When a physician identifies the abnormalities manually, it takes a long time. Since default values are set in the code, we will be able to identify brain abnormalities automatically in this method. When a real-time parameter is compared with the default value, it determines whether the patient is healthy or unhealthy. With the help of a wireless headset, EEG signals are extracted from a normal person and an epileptic, and the signals are then filtered to distinguish between the two. A signal's frequency is used to distinguish it from another signal. Amplitude was a feature for detecting epilepsy. Through the filters, analog signals are converted into 240 samples per second of digital signals. Detecting seizures requires setting a threshold for each signal. Whenever a signal is obtained, the threshold voltage is compared with it. Signals that exceed the threshold light up the LEDs, indicating the start of a seizure. Preventative measures can be taken in a timely manner to reduce the effects of seizure further. For this application, LabVIEW implements a reliable TCP protocol. Using the proposed Tele-monitoring application, specialists can monitor their patients' vital parameters remotely, in real-time, on a Web page and they don't need special requirements on their PC to use the application.

REFERENCES

[1] Abdulbaqi, A.S., Nejrs, S.M., Mahmood, S.D., Panessai, I.Y. (2020). A tele encephalopathy diagnosis based on EEG signal compression and encryption. In International Conference on Advances in Cyber Security, Penang, Malaysia, 1347: 148-166. https://doi.org/10.1007/978-981-33-6835-4_10

[2] Jegan, R., Nimi, W.S. (2017). Low cost and improved performance measures on filtering techniques for ECG signal processing and TCP/IP based monitoring using LabVIEW. In 2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, pp. 1-7. https://doi.org/10.1109/icaccs.2017.8014582

[3] Wadekar, R.S., Kasambe, P.V., Rathod, S.S. (2017). Development of LabVIEW platform for EEG signal analysis. In 2017 International Conference on Intelligent Computing and Control (I2C2), Coimbatore, India, pp. 1-5. https://doi.org/10.1109/i2c2.2017.8321942

[4] Sulaiman, N., Ying, B.S., Mustafa, M., Jadin, M.S. (2018). Offline LabVIEW-based EEG signals analysis for human stress monitoring. In 2018 9th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, pp. 126-131. https://doi.org/10.1109/ICSGRC.2018.8657606

[5] Babu, C.G., Kumar, R.H., Sampath, P., Bhuvaneshwari, P., Dharanya, M. (2018). Analysis of conscious alert system from EEG data using LabView. In 2018

International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, pp. 1-3. https://doi.org/10.1109/iccci.2018.8441260
[6] Barsy, B.G., Győri, G., Szemes, P.T. (2020). Development of EEG measurement and processing system in LabVIEW development environment. International Review of Applied Sciences and Engineering, 11(3): 287-297. https://doi.org/10.1556/1848.2020.00151
[7] Abdulbaqi, A.S., Younis, M.T., Younus, Y.T., Obaid, A.J. (2022). A hybrid technique for EEG signals evaluation and classification as a step towards to neurological and cerebral disorders diagnosis. International Journal of Nonlinear Analysis and Applications, 13(1): 73-781. http://dx.doi.org/10.22075/IJNAA.2022.5590
[8] Rușanu, O.A., Cristea, L., Luculescu, M.C. (2020). LabVIEW and Android BCI chat app controlled by voluntary eye-blinks using neurosky mindwave mobile EEG headset. In 2020 International Conference on e-Health and Bioengineering (EHB), Iasi, Romania, pp. 1-4. https://doi.org/10.1109/ehb50910.2020.9280193
[9] Paszkiel, S., Paszkiel, S. (2020). Using BCI technology for controlling a mobile vehicle using LabVIEW environment. Analysis and Classification of EEG Signals for Brain-Computer Interfaces, 852: 79-86. https://doi.org/10.1007/978-3-030-30581-9_9
[10] Rodríguez-Quiñonez, J.C., Real-Moreno, O. (2022). Structures-LabVIEW™ features. graphical programming using LabVIEW™: Fundamentals and Advanced Techniques, 46: 65-75. https://doi.org/10.1049/pbpc046e_ch5
[11] Sulaiman, N., Goh, K.S., Rashid, M., Jadin, S., Mustafa, M., Ibrahim, M.Z., Samsuri, F. (2020). Offline LabVIEW-based EEG signals analysis to detect vehicle driver microsleep. In Enhancing Health and Sports Performance by Design: Proceedings of the 2019 Movement, Health & Exercise (MoHE) and International Sports Science Conference (ISSC), pp. 271-289. https://doi.org/10.1007/978-981-15-3270-2_29
[12] Al-Barzinji, S.M., Al-din, M.S., Abdulbaqi, A.S., Bhushan, B., Obaid, A.J. (2023). A brain seizure diagnosing remotely based on EEG signal compression and encryption: A step for telehealth. In Artificial Intelligence for Smart Healthcare, pp. 211-225. https://doi.org/10.1007/978-3-031-23602-0_13.
[13] Sangeetha, S.K.B., Mathivanan, S.K., Muthukumaran, V., Pughazendi, N., Jayagopal, P., Uddin, M.S. (2023). A deep learning approach to detect microsleep using various forms of EEG signal. Mathematical Problems in Engineering, 2023(1): 7317938. https://doi.org/10.1155/2023/7317938
[14] Guo, Y., Ding, H., ShangGuan, X. (2023). An XGBoost approach to detect driver visual distraction based on vehicle dynamics. Traffic Injury Prevention, 24(6): 458-465. https://doi.org/10.1080/15389588.2023.2218513
[15] Wang, H., Bi, L., Fei, W., Wang, L. (2019). An EEG-based multi-classification method of braking intentions for driver-vehicle interaction. In 2019 IEEE International Conference on Real-time Computing and Robotics (RCAR), Irkutsk, Russia, pp. 438-441. https://doi.org/10.1109/rcar47638.2019.9044151
[16] Soon, C.S., Vinogradova, K., Ong, J.L., Calhoun, V.D., Liu, T., Zhou, J.H., Ng, K.K., Chee, M.W.L. (2021). Respiratory, cardiac, EEG, BOLD signals and functional connectivity over multiple microsleep episodes. NeuroImage, 237: 118129. https://doi.org/10.1016/j.neuroimage.2021.118129
[17] Zubair, M. (2021). Classification of alcoholic and non-alcoholic EEG signals based on sliding-SSA and independent component analysis. TechRxiv. https://doi.org/10.36227/techrxiv.14837226.v1
[18] Bonfati, L.V., Mendes Junior, J.J., Siqueira, H.V., Stevan Jr, S.L. (2022). Correlation analysis of in-vehicle sensors data and driver signals in identifying driving and driver behaviors. Sensors, 23(1): 263. https://doi.org/10.3390/s23010263
[19] Hu, J., Liu, Y., Liang, X., Yu, Y., Zeng, L.L. (2023). Driver steering intention prediction based on fusion of EEG and eye movement signals. In 2023 China Automation Congress (CAC), Chongqing, China, pp. 8306-8310. https://doi.org/10.1109/CAC59555.2023.10451053
[20] Abdulkareem, H.A., Al-Faiz, M.Z. (2019). Offline linear discriminant analysis classification of two class EEG signals. Iraqi Journal of Information and Communication Technology, 2(3): 1-10. https://doi.org/10.31987/ijict.2.3.71
[21] Gangone, J.B.K. (2019). An ineligible and unauthorized motor vehicle driver access control and sleep state alert system: An offline based model. In 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, pp. 1-6. https://doi.org/10.1109/icccnt45670.2019.8944492
[22] Lestyán, S., Acs, G., Biczók, G., Szalay, Z. (2019). Extracting vehicle sensor signals from can logs for driver Re-identification. In Proceedings of the 5th International Conference on Information Systems Security and Privacy, 1: 136-145. https://doi.org/10.5220/0007389501360145
[23] Kulkarni, A.M., Nandi, A.V., Nissimagoudar, P.C. (2019). Driver state analysis for ADAS using EEG signals. In 2019 2nd International Conference on Signal Processing and Communication (ICSPC), Coimbatore, India, pp. 26-30. https://doi.org/10.1109/icspc46172.2019.8976799
[24] Almogbel, M.A., Dang, A.H., Kameyama, W. (2019). Cognitive workload detection from raw EEG-signals of vehicle driver using deep learning. In 2019 21st International Conference on Advanced Communication Technology (ICACT), PyeongChang, Korea (South), pp. 1-6. https://doi.org/10.23919/icact.2019.8702048
[25] Sivakumar, P., Selvaraj, J., Ramaraj, K., Sahayadhas, A. (2021). Analysis of alpha and theta band to detect driver drowsiness using electroencephalogram (EEG) signals. The International Arab Journal of Information Technology, 18(4): 578-584. https://doi.org/10.34028/18/4/10
[26] Gangone, J.B.K. (2020). An offline-based intelligent motor vehicle driver behavior analysis using driver's eye movements and an inexperienced and unauthorized driver access control mechanism. In Cybernetics, Cognition and Machine Learning Applications: Proceedings of ICCCMLA 2019, pp. 225-233. https://doi.org/10.1007/978-981-15-1632-0_21
[27] Ettahiri, H., Ferrández Vicente, J.M., Fechtali, T. (2022). EEG brain signals to detect the sleep health of a driver:

An automated framework system based on deep learning. Frontiers in Human Neuroscience, 16: 915276. https://doi.org/10.3389/fnhum.2022.915276
[28] Shangguan, P., Qiu, T., Liu, T., Zou, S., Liu, Z., Zhang, S. (2020). Feature extraction of EEG signals based on functional data analysis and its application to recognition of driver fatigue state. Physiological Measurement, 41(12): 125004. https://doi.org/10.1088/1361-6579/abc66e
[29] Quintero-Rincón, A., Muro, V., d'Giano, C., Prendes, J., Batatia, H. (2020). Statistical model-based classification to detect patient-specific spike-and-wave in EEG signals. Computers, 9(4): 85. https://doi.org/10.3390/computers9040085
[30] Qazi, E.U.H., Hussain, M., AboAlsamh, H.A. (2021). Electroencephalogram (EEG) Brain signals to detect alcoholism based on deep learning. Computers, Materials & Continua, 67(3): 3329-3348. https://doi.org/10.32604/cmc.2021.013589