Brain signals analysis for sleep stages detection using virtual instrumentation platform

Abdeljalil El Hadiri, Lhoussain Bahatti, Abdelmounime El Magri, Rachid Lajouad
Laboratory of Electrical Engineering and Intelligent Systems, ENSET Mohamedia, Hassan II University of Casablanca, Mohammedia, Morocco

Article Info

Article history:

Received Aug 4, 2022
Revised Oct 11, 2022
Accepted Oct 24, 2022

Keywords:

Electroencephalogram
LabVIEW
Real time
Signal processing
Sleep detection

ABSTRACT

This paper discusses the use of the laboratory virtual instrumentation engineering workbench (LabVIEW) software tool for analyzing brain waveforms (i.e EEG: electroencephalogram) to study sleep stages such as deep sleep, light sleep and so on. The used EEG signals are generated in order to span all sleeping phases. Indeed, a mandatory step of signal processing has been performed, such as sampling, filtering and features extraction. This analysis is carried out with the LabVIEW program, which is a popular virtual instrumentation platform. The EEG signals used in the analysis were obtained from an open-source database and went through several steps, including noise removal, classification and feature extraction. To extract the feature, different filters are employed and the outputs of all filters are compared, leading to a sleep level detection. The simulation results show clearly the performances of this analysis.

Corresponding Author:

Abdeljalil El Hadiri
Laboratory of Electrical Engineering and Intelligent Systems, ENSET Mohamedia
Hassan II University of Casablanca
Boulevard Hassan II, Mohammedia BP 159, Morocco
Email: abdeljalil.elhadiri-etu@etu.univh2c.ma

1. INTRODUCTION

Safety is a fundamental issue for all road users, particularly vehicle drivers, as traffic accidents occur around the world, resulting in significant losses ranging from serious injury to death [1]–[3]. Strong management in all areas of safety on the road is essential for achieving effective road safety outcomes. It is suggested that a financed lead agency is in place to drive the national road safety effort and execute a Safe Systems strategy. The government only has a significant road safety goal, which is to minimize deaths by 20% and 50%, accordingly, between 2016 and 2020 and 2016 and 2026 [4], In the statistical situation of road safety in Morocco, data on traffic accidents and their victims are mainly derived from field observations and statistics compiled by government agencies [5], In this context, the Moroccan Ministry of Equipment and Transport, declared that there were more than 67,300 accidents, 2500 fatal accidents, 3026 people killed, 10037 people seriously injured, and 92366 people potentially suffering injuries [6].

Driver sleepiness is currently one of the main causes of of fatal accidents [7]. Many accidents can be averted if tiredness is identified and communicated to the driver as a mental state. As a result, driver drowsiness and the time of falling asleep can be detected. All of these possibilities have resulted in the establishment of a human drowsy state surveillance system for drivers, which has become a key emphasis subject in the field of safe driving [8].

Researchers have developed various techniques to identify drowsiness, Several of these approaches are extremely accurate, such as, detecting eyes blinking, detecting mouth [9]-[12] and detecting faces from videos or photo [13]-[15], the majority of these solutions utilised computer vision algorithms. various algorithms are employed to identify tiredness and raise the alarm after recognising the face, eyes, and mouth. Many methods have a high level of accuracy. Color of skin, lighting, wearing glasses, are all downsides of some approaches.

Electroencephalogram (EEG) is the term for these signals to be recorded. It’s is a device that monitors and measures the various electrical processes in the brain [16]. These signals are measured with electrodes positioned in the scalp. As illustrated in Figure 1, the standardized EEG set-up is based on the 10-20 electrodes defined by the international federation (IF) in 1958 [17].

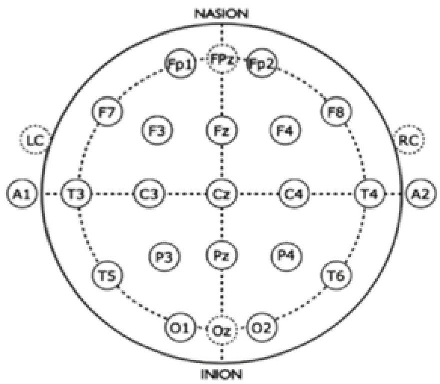

Figure 1. 10–20 Electrode placement system [18]

The Alpha band, Beta band, Theta band, Delta band, Gamma band, and Mu band are the six frequency bands of brain waves [19], [20]. EEG signals provide vital information about the brain and body's functioning. It is now feasible to study sleep by evaluating the EEG signal and identifying the stages of weariness and insomnia. Nevertheless, irregular and It's challenging to interpret what these non-stationary signals represent by looking at them. As a result, assembling the necessary data in an intelligible format from these recorded signals must be processed following the aim. Furthermore, Signal analysis is made considerably more difficult by noise from the equipment employed.

In this paper, we create a platform that would allow users to obtain and record EEG signals and evaluate them using laboratory virtual instrumentation engineering workbench (LabVIEW) software. Delta band, theta band, alpha band, and beta band were generated from the EEG data Figure 2. There are two main forms of noise in the original EEG signal: physiological and physical [21]. We also go over signal conditioning and signal processing to create a platform for detecting problems in EEG signals and remote monitoring utilizing characteristics like mean, standard deviation and variance via EEG and LabVIEW.

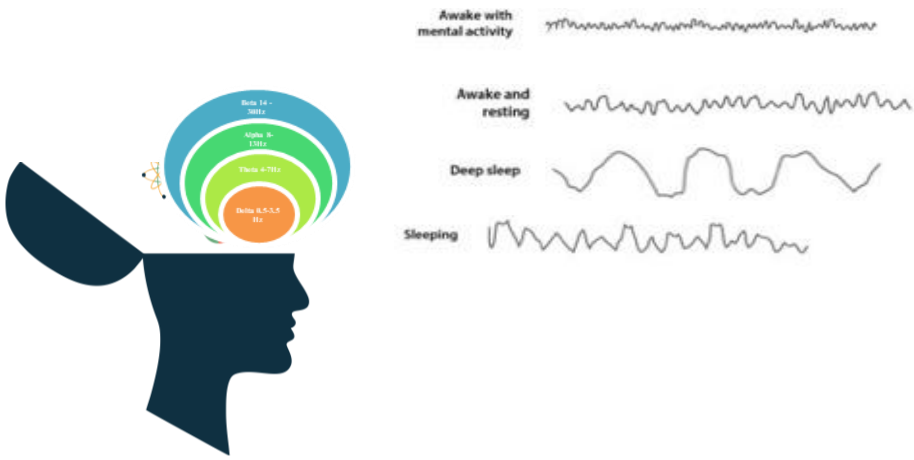

Figure 2. Brain waves and frequency band

This paper is organized as shown in. Section 2 presents the methodology used to detect the different stages of sleep. Section 3 highlights the simulation of the proposed LabVIEW interface and the obtained results. The conclusion of this paper is discussed in Section 4.

2. MATERIAL AND METHOD
2.1. Software
Today's popular software development tools, like as visual basic and visual C++, need extensive code compilation, which can be a challenge for BCI designers who aren't experienced with programming. national instruments' (NI) LabVIEW is the solution to this dilemma. LabVIEW is a software platform that is based on graphics. It was created by the National Instruments Company in the United States. The use of program is becoming more common in engineering and signal processing applications [22]-[25]. It offers a visual interface for algorithm development. Physical elements like oscilloscopes and multimeters are used to model LabVIEW's architecture and operations.

As it is often used in signal processing subjects, LabVIEW software was chosen [26], [27]. It's more user-friendly than text-based programs. As a result, it reduces developers time and effort. LabVIEW has become a common tool for data collecting and research laboratories, academia, and instrument control in healthcare industry [28].

As a result, the number of users is gradually expanding. It is generally preferred, especially in biomedical sectors, due to graphical representation and Biomedical Toolkits. You may simply and successfully take EEG, EMG, and ECG data with the Biomedical Toolkit and analyze their signals in LabVIEW [29].

The block diagram and the front panel are the two parts of LabVIEW. The latter software was identified as the best platform for processing EEG signals. National Instruments' LabVIEW software is a virtual instrumentation engineering workstation. i) data collecting, ii) data analysis, and iii) visualization of the data are the three components of this graphical programming. Virtual instruments are the names given to the functions in LabVIEW (VIs). LabVIEW programming was concerned with providing an efficient and convenient environment for code creation, particularly when the user has to interact with the program and see the outcomes [30]-[32].

2.2. EEG signal analysis
The analysis of the EEG signal has been generally investigated due to its capacity to provide an objectively record method of brain stimulation, that is frequently applied in brain-computer interface studies with applications in health care diagnosis. Manipulation of the acquired EEG signal allows for easy analysis and investigation of brain activity since EEG helps to highlight the existing state of the individual whether asleep, or even awake. The proposed LabVIEW application's implementation, which consists of several novel virtual instruments that aim to integrate the four phases that go into creating a sleep detection interface system: importing the EEG signal from an open-source database, processing and extracting the features, and then classifying the filtered signal to detect the corresponding sleep stage, is the main original contribution of this paper Figure 3.

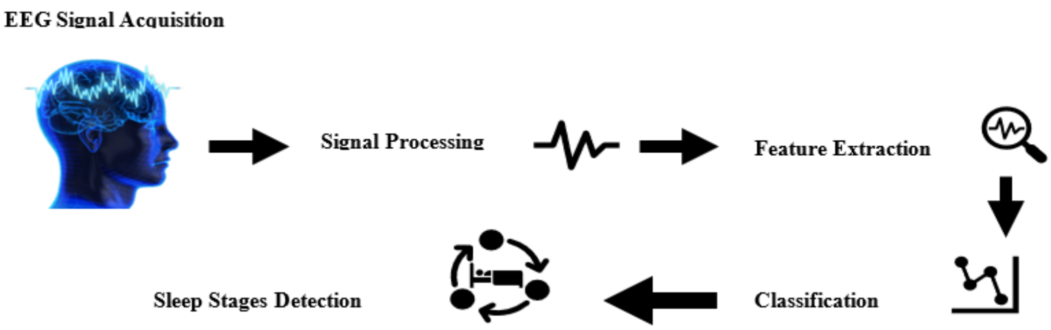

Figure 3. Steps of EEG signal analysis and sleep state detection

2.2.1. EEG data acquisition
A set of raw EEG data is taken from the open-source database [33] as .edf file to feed at the input of the biomedical toolkit in LabVIEW software for analyzing and identifying the different features of EEG

signals. This database provides comprises a significant number of recordings of EEG signals obtained from many different people under various conditions. The output of the simulated EEG signal contains a variety of frequency bands as follows beta, alpha, delta, and theta frequency band. Each of these frequency wavebands determines different electrical activities of neurons indicating different sleep states.

There are five frequency bands in the EEG waveform: respectively δ, θ, α, β and γ. These bands can provide useful information for the diagnosis, monitoring, and the treatment of neural diseases and features. Table 1 depicts the signal amplitude and various frequency ranges of an EEG signal.

Table 1. Amplitude and frequency range of decomposed EEG signal

Bands	Frequencies (Hz)	Amplitude(μV)
Delta (δ)	0–4 Hz	20–100
Theta (θ)	4–8 Hz	10
Alpha (α)	8–13 Hz	2–100
Beta (β)	13–22 Hz	5–10
Gamma (γ)	> 30	-

2.2.2. Signal processing

The recorded EEG signal has significant artifacts and noise, affecting the accuracy and performance of the project. Hence, a signal pre-processing is implemented before moving on to the next step of the sleep phase detection. The EEG signal goes through three phases of preprocessing:

a. Sampling

The EEG signal retrieved from the databases comprises a considerable quantity of data that LabVIEW cannot analyze directly. As a result, the constructed waveform functional block samples the input EEG signal. The output is then utilized to evaluate the data.

b. Pre-amplification

Electroencephalograms (EEGs) are weakly amplifiable biosignals that are distorted by electrode-skin interferences and low-frequency noise. A biomedical signal acquisition system's analogue front end must therefore include a preamplifier stage. However, the amplifier must be able to reject noise and interferences in order to only amplify the physiological signal while maintaining a high signal-to-noise ratio. The acquired EEG data has very low amplitudes and is difficult to directly analyze. To enhance the signal's amplitude, it is pre-amplified using a multiplier block.

c. Filtering

Filtering signals is a basic concept in EEG signal analysis, and several EEG filters, such as FIR and IIR filters, are available in LabVIEW. FIR filters offer a linear phase response, while IIR filters produce a non-linear phase response [34]. As a result, FIR filters can be employed in applications which phase information is required, while IIR filters can be used in applications where phase information is not required.

$$y[n] = \sum_{k=0}^{N} b_k x[n-k] \tag{1}$$

An FIR filter is written as a difference equation, with b's being the filter coefficients and N denoting the number of zeros or filter order. An FIR filter generates a current output $y[n]$ by operating on a current input $x[n]$ and a number of past inputs $x[n-k]$ as indicated by this equation. An IIR filter's difference equation is expressed by

$$y[n] = \sum_{k=0}^{N} b_k x[n-k] - \sum_{k=1}^{M} a_k y[n-k] \tag{2}$$

The filter coefficients are denoted by b's and a's, while the number of zeros and poles are denoted by N and M, accordingly. An IIR filter, as shown in (3), generates a current output $y[n]$ by combining a number of prior outputs $y[n-k]$, and also a current and a number of past inputs. An IIR filter's transfer function is written as:

$$H(z) = \frac{b_0 + b_1 z^{-1} + \cdots + b_N z^{-N}}{1 + a_1 z^{-1} + \cdots + a_M z^{-M}} \tag{3}$$

The most significant distinction between finite impulse response (FIR) and infinite impulse response (IIR) filters is the impulse response, which is finite for FIR filters and unlimited for IIR filters. When compared to IIR filters, FIR filters often require more multiplications and summations for the same filtering effectiveness. Since certain computer architectures are better suited for digital computation than others, such as digital signal processors (DSPs), certain computer architectures are better suited for FIR filtering. The FIR filter has a substantially faster processing speed than the IIR filter. When compared to FIR filters, IIR filters always yield very high co-efficient values, and because there are so many co-efficients accessible, computations are simple [35].

The brain signal is affected when collecting data from the subject due to noise caused mainly by electricity in the electrodes. Since electricity is transferred at this frequency, this noise is most common at 50 Hz. By passing the signal through a Butterworth low-pass filter with a cut-off frequency of 30 Hz, this noise can be eliminated. This filter has a strong capability to show nonlinear phase response. In addition, it serves as a good bandpass for its better responsively to frequency. Depending on the output requirement, the filter is configured with different cut-off frequencies (low and high). The bandpass filter was tuned to a lower cutoff frequency of 0.5 Hz and an upper cutoff frequency of 4 Hz to obtain the delta signal. A lower cut-off frequency of 4 Hz and an upper cut-off frequency of 8 Hz are chosen for the Theta brainwave. A lower cutoff frequency of 8 Hz and an upper cutoff frequency of 13 Hz are established for the Alpha brainwave band, while a lower cutoff frequency of 13 Hz and an upper-frequency band of 30 Hz are set for the Beta brainwave band. Predefined filters are already included in LabVIEW and can be used without the need to redefine them.

2.2.3. Feature extraction

This section is devoted to feature extraction, which is the process of characterizing electroencephalography (EEG) signals by a core set of values representing the pertinent data they include in order to later identify them. It investigates what data should be extracted from EEG signals and how to do it in order to distinguish between various sleep states as accurately as possible. The process of describing a collection of features is called feature extraction. The most effective analysis can be provided by feature extraction. The major goal is to gather trustworthy data for signal classification and efficient analysis. The mean, standard deviation, and variance of the EEG signal were considered as sleep extracted features in this study.

a. Mean (μ)

The Mean of the signal is the ratio of the sum of all of the signal's values to the overall size of the signal [36], The formula for calculating the mean is presented in (4):

$$Mean\ (\mu) = \frac{1}{N}\sum_{n=1}^{N} Xn \tag{4}$$

where μ is the signal mean and $\{X1, \dots, Xn\}$ are the signal values.

b. Standard deviation (SD)

The Standard Deviation is a statistical feature that reveals how the data is distributed in relation to the mean [37]. According to (5) shows the formula for calculating SD.

$$Standard\ Deviation(SD) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi - \mu)2} \tag{5}$$

Where, μ denotes the mean or average and the length of the EEG data is indicated by the number N.

c. Variance (σ)

The variance is a statistical measurement of the dispersion of a probability variable [38]. It is designated by:

$$Variance(\sigma) = \frac{1}{N}\sum_{i=1}^{N}(Xi - \mu)2 \tag{6}$$

where:
μ is the mean of the signal
N signifies the length of EEG data
The length of the EEG data is indicated by the number N.

The mean, standard deviation and variance are applicable to the power spectrum of EEG beta, alpha, theta, and delta bands in order to find the sleep feature. Fourier transform and power spectral density (PSD) algorithms in LabVIEW are used to determine the power spectrum of EEG signals. The power spectrum and power spectral density equation are presented in (7) and (8) respectively.

$$X(k) = \sum_{n=0}^{N-1} x(nTs)e^{-\frac{j2\pi nk}{N}}\ ; k\ =\ 0, \ldots \ldots, N-1 \tag{7}$$

$$PSD = |X(k)|^2 = \left|\sum_{n=0}^{N-1} x(nTs)e^{-\frac{j2\pi nk}{N}}\right|^2 \tag{8}$$

The EEG signals, as previously stated, contain components in four different frequency bands. In process for extracting the signal's features in several frequency bands, to investigate the signal as a result, categorization of these signals is necessary. The four-band pass is used to separate those frequency bands. Cutoff frequencies for filters based on the band range.

The average amplitude of the delta, theta, alpha, and beta bands is calculated using the mean vi module in this stage. The standard deviation mean of the amplitudes of each wave band is taken by the mean vi module, which then passes through a constructed array module that connects many elements. The array collects all of the wave's mean amplitudes and compares them. After that, the mean amplitude values are compared to obtain the maximum mean among them. The calculated result is displayed in this maximum mean to a string. If the estimated dominant value corresponds to the Delta waveband, for example, the drowsy condition is displayed. Similarly, the drowsy condition is displayed if the dominating value corresponds to the Theta waveband.

2.2.4. Classification

All of the frequency bands have different band ranges and sleep stages, Table 2. The type of EEG signal is determined by the amount of mean amplitude acquired for each frequency band. The base-band signal has the highest maximum amplitude, and the appropriate sleep stages may be detected.

Table 2. sleep stages and corresponding frequency band

Sleep Stages	Frequency band	States
Stage 1	8 -13 Hz	Drowsiness
Stage 2	4 - 8 Hz	Deep Sleep
Stage 3 and 4	0.5 - 4 Hz	Light Sleep
Awake Stage	13 - 30 Hz	Awake

2.2.5. Flowchart

With a rise in the frequency spectrum of electrical activity of brainwave bands, EEG suggests sleepiness. EEG is employed as a reference indication because of its accuracy in detecting drowsiness, which defines the subject's mental state. This is due to the fact that the brain determines a person's exact condition. However, the EEG result will depend on the person's other problems.

In our simulation, we used the biomedical tools in LabVIEW to produce the EEG signal. The data collected from the signal is processed via an IIR Butterworth band pass signal with various frequency ranges. The Delta, Theta, Alpha, and Beta bands are formed as a result of this. We assess which bands are the most dominant after we have the bands.

3 RESULTS AND DISCUSSION

The model of the studied detector of sleep stage is structured on labview Figure 4, in order to determine different stage of drowsiness. Using LabVIEW, the recorded EEG signal is processed using IIR-type bandpass filters, and the output data are compared to determine the states of the human brain. The Labview interface is plotted on the front panel in Figure 5. The front panel results for the sleepiness data 1 are illustrated in Figure 6.

The frequency and amplitude values of the four primary wavebands Delta, Theta, Alpha and Beta are identified and Averaged from the raw EEG data. The highest average is determined from these four average values, thus revealing the dominant waveband. The delta, theta, alpha, and beta bands, for instance, have frequencies of 1.96 Hz, 7.27 Hz, 8.82 Hz, and 14.35 Hz, respectively, and average values of 3.99, 2.02, 2.89, and 1.01 units in Sample 1. The highest average of these four averages denotes the Delta waveband.

Therefore, we could deduce that the individual is in a light sleep state because the Delta band is prominent. The mean value of the different EEG signals and the maximum value are presented in Table 3 along with the sleep state of the subjects.

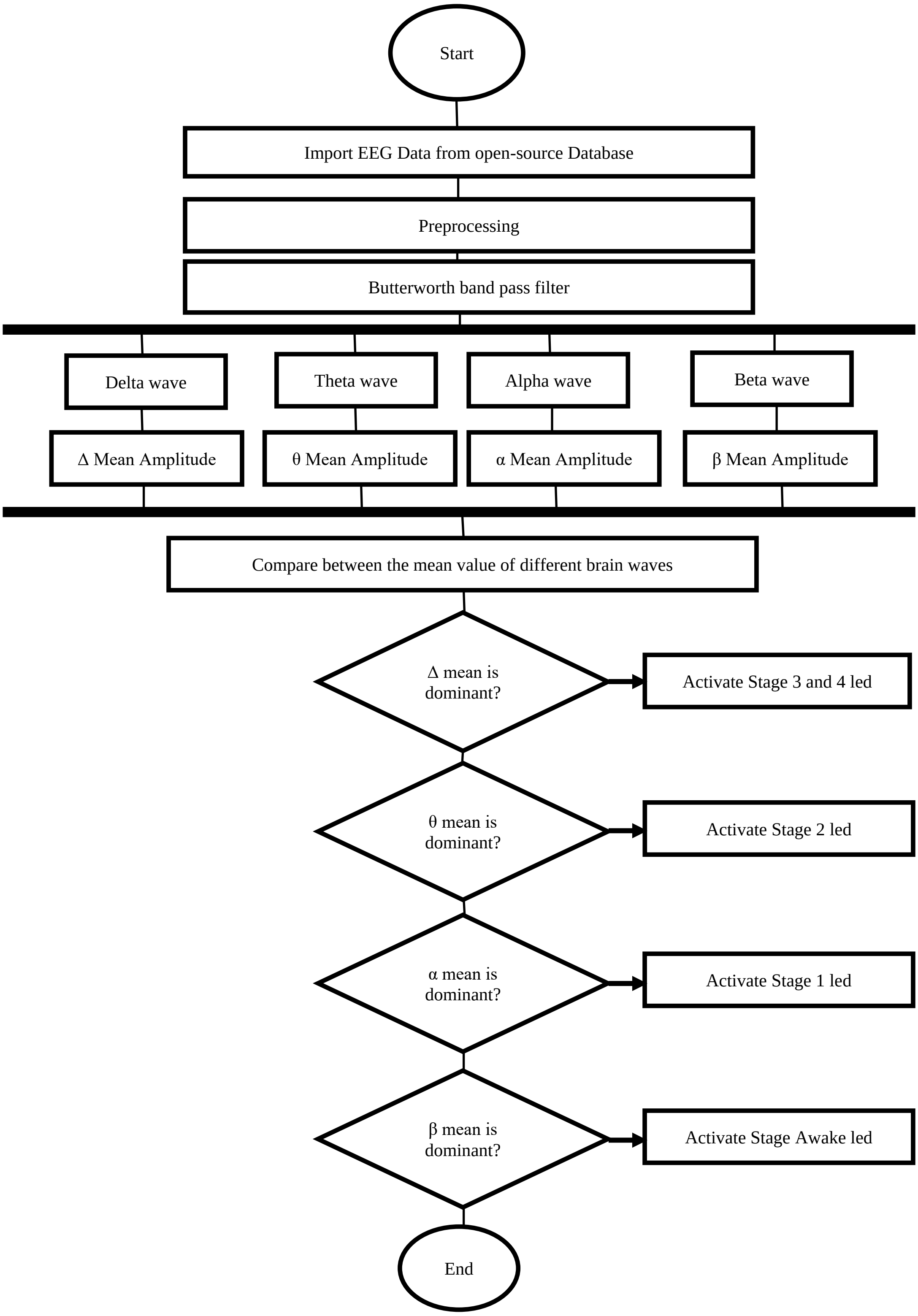

Figure 4. Flowchart for sleep detection interface

Figure 5. Labview front panel for sleep stages detection

Figure 6. Front panel showing the result of EEG analysis and sleep detection for subject 1

Table 3. The result obtained from the simulation of the LabVIEW interface for the different subject

Subjects Data	Mind Waves	Frequency Measured	Amplitude Measured		Dominant wave	Sleep stages
			Mean Value of wave band	Maximum Value		
Sb.1	Delta	1.96	3.99	3.99	Delta	Light sleep
	Theta	7.27	2.02			
	Alpha	8.82	2.89			
	Beta	14.35	1.01			
Sb.2	Delta	1.35	3.69	4.24	Alpha	Relaxed & Drowsiness
	Theta	7.04	2.72			
	Alpha	8.73	4.24			
	Beta	14.70	1.02			
Sb.3	Delta	1.35	27.62	30.35	Theta	Deep Sleep
	Theta	4.52	30.35			
	Alpha	8.48	14.51			
	Beta	20.63	11.33			
Sb.4	Delta	1.06	3.43	3.43	Delta	Light sleep
	Theta	4.85	1.43			
	Alpha	8.73	1.32			
	Beta	14.07	0.95			
Sb.5	Delta	2.12	5.68	7.25	Beta	Awake
	Theta	5.76	4.31			
	Alpha	11.29	5.25			
	Beta	21.40	7.25			

4. CONCLUSION

This work has established a user interface on LabVIEW for sleep stage classification, using measurement EEG data from an open source and fundamental physical prior about the EEG signal. The first design step involves the choice of the visual programming language LabVIEW to create the user interface. In a second independent step, EEG data were analyzed in the time, frequency and time-frequency domains using the generated interface. The methodology delivers the state of the drowsiness by extracting the characteristics of the EEG signal and comparing them to the signal's mean value. The suggested interface and algorithm collect information from the EEG channel and also can distinguish between the Alert and Drowsy states.

REFERENCES

[1] S. Kar, M. Bhagat, and A. Routray, “EEG signal analysis for the assessment and quantification of driver’s fatigue,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 13, no. 5, pp. 297–306, Sep. 2010, doi: 10.1016/j.trf.2010.06.006.

[2] A. Sonnleitner, M. Simon, W. E. Kincses, A. Buchner, and M. Schrauf, “Alpha spindles as neurophysiological correlates indicating attentional shift in a simulated driving task,” *International Journal of Psychophysiology*, vol. 83, no. 1, pp. 110–118, Jan. 2012, doi: 10.1016/j.ijpsycho.2011.10.013.

[3] W. Li, Q. C. He, X. M. Fan, and Z. M. Fei, “Evaluation of driver fatigue on two channels of EEG data,” *Neuroscience Letters*, vol. 506, no. 2, pp. 235–239, Jan. 2012, doi: 10.1016/j.neulet.2011.11.014.

[4] Global Road Safety Facility (GRSF), “Road Safety in Ghana | Traffic accidents, crash, fatalities & injury statistics ,” *Roadsafetyfacility.org*, 2020. https://www.roadsafetyfacility.org/country/ghana (accessed Mar. 07, 2022).

[5] K. Ouazzani-Touhami and N. Souissi, “Simulation project life cycle applied to road safety: A case study of morocco,” in *Colloquium in Information Science and Technology, CIST*, 2020, vol. 2020-June, doi: 10.1109/CiSt49399.2021.9357252.

[6] A. M. Addi, A. Tarik, and G. Fatima, “An approach based on association rules mining to improve road safety in Morocco,” in *2016 International Conference on Information Technology for Organizations Development, IT4OD 2016*, Mar. 2016, pp. 1–6, doi: 10.1109/IT4OD.2016.7479311.

[7] L. Salvati, M. D’amore, A. Fiorentino, A. Pellegrino, P. Sena, and F. Villecco, “On-road detection of driver fatigue and drowsiness during medium-distance journeys,” *Entropy*, vol. 23, no. 2, pp. 1–12, Jan. 2021, doi: 10.3390/e23020135.

[8] D. Mahalingam, P. Rajkumar, R. B. Priya, and P. Sudha, “Real Time Monitoring for Drowsiness Detection using EEG System,” *International Journal of Electronics and Communication Engineering*, vol. 2, no. 5, pp. 42–44, Feb. 2015, doi: 10.14445/23488549/ijece-v2i5p113.

[9] A. Rahman, M. Sirshar, and A. Khan, “Real time drowsiness detection using eye blink monitoring,” in *2015 National Software Engineering Conference, NSEC 2015*, Dec. 2016, pp. 1–7, doi: 10.1109/NSEC.2015.7396336.

[10] K. Dwivedi, K. Biswaranjan, and A. Sethi, “Drowsy driver detection using representation learning,” in *Souvenir of the 2014 IEEE International Advance Computing Conference, IACC 2014*, Feb. 2014, pp. 995–999, doi: 10.1109/IAdCC.2014.6779459.

[11] Z. Zhang and J. Zhang, “A new real-time eye tracking based on nonlinear unscented Kalman filter for monitoring driver fatigue,” *Journal of Control Theory and Applications*, vol. 8, no. 2, pp. 181–188, May 2010, doi: 10.1007/s11768-010-8043-0.

[12] L. M. Bergasa and J. Nuevo, “Real-time system for monitoring driver vigilance,” in *IEEE International Symposium on Industrial Electronics*, 2005, vol. III, pp. 1303–1308, doi: 10.1109/ISIE.2005.1529113.

[13] H. A. Rowley, S. Baluja, and T. Kanade, “Neural network-based face detection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 1, pp. 23–38, 1998, doi: 10.1109/34.655647.

[14] P. Viola and M. J. Jones, “Robust Real-Time Face Detection,” *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, May 2004, doi: 10.1023/B:VISI.0000013087.49260.fb.

[15] B. N. Manu, “Facial features monitoring for real time drowsiness detection,” in *2016 12th International Conference on Innovations in Information Technology (IIT)*, Nov. 2016, pp. 1–4, doi: 10.1109/INNOVATIONS.2016.7880030.

[16] B. Gaddipati, U. R. Nelakuditi, and J. W. C. Medithe, “Single lead EEG acquisition system for health care applications,” in *Proceedings of the International Conference on Inventive Computation Technologies, ICICT 2016*, Aug. 2016, vol. 1, pp. 1–4, doi: 10.1109/INVENTIVE.2016.7823238.

[17] K. GH, L. HO, J. HH, and E. C, “The ten-twenty electrode system of the International Federation. The International Federation of Clinical Neurophysiology.,” *Electroencephalography and Clinical neurophysiology. Supplement*, vol. 52, pp. 3–6, 1999, [Online]. Available: https://europepmc.org/article/med/10590970.

[18] M. Hassib, “Mental task classification using single-electrode brain computer interfaces,” Master's of Thesis, Universität Stuttgart, 2012.

[19] M. Teplan and Institute, “Fundamentals of Eeg Measurement,” *AAAI Fall Symposium - Technical Report*, vol. FS-12-04, no. 2, pp. 59–64, 2012.

[20] M. Murugappan and S. Murugappan, “Human emotion recognition through short time Electroencephalogram (EEG) signals using Fast Fourier Transform (FFT),” in *2013 IEEE 9th International Colloquium on Signal Processing and its Applications*, Mar. 2013, pp. 289–294, doi: 10.1109/CSPA.2013.6530058.

[21] H. Ghandeharion and A. Erfanian, “A fully automatic ocular artifact suppression from EEG data using higher order statistics: Improved performance by wavelet analysis,” *Medical Engineering & Physics*, vol. 32, no. 7, pp. 720–729, Sep. 2010, doi: 10.1016/j.medengphy.2010.04.010.

[22] H. Guler, I. Turkoglu, and F. Ata, “Designing intelligent mechanical ventilator and user interface using LabVIEW®,” *Arabian Journal for Science and Engineering*, vol. 39, no. 6, pp. 4805–4813, Jun. 2014, doi: 10.1007/s13369-014-1090-y.

[23] H. Güler and F. Ata, “Design and implementation of training mechanical ventilator set for clinicians and students,” *Procedia - Social and Behavioral Sciences*, vol. 83, pp. 493–496, Jul. 2013, doi: 10.1016/j.sbspro.2013.06.095.

[24] H. Guler and F. Ata, “The comparison of manual and LabVIEW-based fuzzy control on mechanical ventilation,” *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, vol. 228, no. 9, pp. 916–925, Sep. 2014, doi: 10.1177/0954411914550513.

[25] C. Dumitrescu, I. M. Costea, C. K. Banica, and S. Potlog, “LabVIEW brain computer interface for EEG analysis during sleep stages,” in *2015 9th International Symposium on Advanced Topics in Electrical Engineering, ATEE 2015*, May 2015, pp. 285–288, doi: 10.1109/ATEE.2015.7133781.

[26] M. N. Mamatha, S. Ramachandran, and M. Chandrasekaran, “Smart sensor design and analysis of brain machine interface using labview,” in *2011 IEEE 3rd International Conference on Communication Software and Networks, ICCSN 2011*, May 2011, pp. 464–468, doi: 10.1109/ICCSN.2011.6014936.

[27] S. Guzel, T. Kaya, and H. Guler, “LabVIEW-based analysis of EEG signals in determination of sleep stages,” in *2015 23rd Signal Processing and Communications Applications Conference, SIU 2015 - Proceedings*, May 2015, pp. 799–802, doi: 10.1109/SIU.2015.7129949.

[28] C. Elliott, V. Vijayakumar, W. Zink, and R. Hansen, “National instruments LabVIEW: A Programming Environment for Laboratory Automation and Measurement,” *Journal of Laboratory Automation*, vol. 12, no. 1, pp. 17–24, Feb. 2007, doi: 10.1016/j.jala.2006.07.012.

[29] Y. Dileep Kumar and A. M. Prasad, “Wavelet analysis of EEG using LABVIEW,” *Indian Journal of Emerging Electronics in Computer Communications*, no. 1, 2016, [Online]. Available: www.scientistlink.com/ijeecc.

[30] V. R. Varada, D. Moolchandani, and A. Rohit, “Measuring and processing the brain ’ s EEG signals with visual feedback for human machine interface,” *International Journal of Scientific & Engineering Research*, vol. 4, no. 1, pp. 1–4, 2013, [Online]. Available: http://www.ijser.org.

[31] Kasarwala J N and W. J. S. & Sanghvi, “Development of single channel EEG using LabVIEW,” *International Journal on Advanced Electrical and Electronics Engineering*, vol. 1, no. 1, pp. 2278–8948, 2012.

[32] W. Zhi-Hao, Hendrick, K. Yu-Fan, C. Chuan-Te, L. Shi-Hao, and J. Gwo-Jia, “Controlling DC motor using eye blink signals based on LabVIEW,” in *Proceeding - 2017 5th International Conference on Electrical, Electronics and Information Engineering: Smart Innovations for Bridging Future Technologies, ICEEIE 2017*, Oct. 2018, vol. 2018-January, pp. 61–65, doi: 10.1109/ICEEIE.2017.8328763.

[33] PhysioNet, “Sleep-EDF Database Expanded,” 2013. https://physionet.org/content/sleep-edfx/1.0.0/ (accessed Mar. 07, 2022).

[34] N. Kehtarnavaz and N. Kim, *Digital Signal Processing System-Level Design Using LabVIEW*. Elsevier, 2005, doi: 10.1016/B978-0-7506-7914-5.X5000-4.

[35] S. N. Hallur, “Epilepsy Detection by Processing of EEG Signals using Labview Simulation,” *International Journal for Research in Applied Science and Engineering Technology*, vol. 6, no. 6, pp. 888–898, Jun. 2018, doi: 10.22214/ijraset.2018.6135.

[36] A. Panat, A. Patil, and G. Deshmukh, “Feature Extraction of Eeg Signals in Different Emotional States,” in *8th IRF International Conference*, 2014, pp. 63–67.

[37] N. Sulaiman *et al.*, “Offline LabVIEW-Based EEG Signals Analysis to Detect Vehicle Driver Microsleep,” in *Lecture Notes in Bioengineering*, 2020, pp. 271–289, doi: 10.1007/978-981-15-3270-2_29.

[38] M. B. V., O. Farooq, and Y. U. Khan, “Automatic seizure detection using higher order moments,” in *2010 International Conference on Recent Trends in Information, Telecommunication and Computing*, Mar. 2010, pp. 159–163, doi: 10.1109/ITC.2010.29.

BIOGRAPHIES OF AUTHORS

Abdeljalil El Hadiri was born in Casablanca, Morocco. In 2016 he had got his license degree in Electrical Engineering and Renewable Energy, at the Superior School of Technology Berrechid -Morocco (ESTB) at the University Hassan I Settat-Morocco, then he had got a Master’s degree in biomedical engineering from FST Settat in 2018. He is currently a PhD student in the Laboratory of Electrical Engineering and Intelligent Systems (EEIS), Hassan II University, Mohammedia-Casablanca, Morocco. His works studies and interests are focused on Bio signal Processing, Soft computing and Embedded systems for biomedical engineering. He can be contacted at email: abdeljalil.elhadiri@gmail.com.

Lhoussain Bahatti was born in 1969 at MIDELT, Morocco. He is now a teacher of electrical engineering and researcher at Hassan II University of Casablanca, ENSET Institute, Mohammedia Morocco. He received the Aggregation Electrical Engineering degree in 1995 from the ENS CACHAN France. He has his Ph.D. degree in 2013 in musical signal processing from the Faculty of Science and Technology of Mohammedia (FSTM). He has published more than 30 research publications in various National, International conference proceedings and Journals on signal processing, control and machine learning. He is a supervisor and Co-supervisor of several PhD students in the field of identification, biomedical signal processing, smart control of renewable energy production systems and pattern recognition. He can be contacted at email bahatti.enset@gmail.com.

Abdelmounime El Magri received the Aggregation of Electrical Engineering from the Normal School of Technical Education (ENSET), Rabat, Morocco, in 2001, the Ph.D. degree in Electrical and control engineering from University Mohammed V, Rabat; in 2011. Currently, he is Professor at the Normal School of Technical Education, Mohammedia, University Hassan II, Casablanca, Morocco. His research interests include nonlinear system identification, nonlinear control, adaptive control, power and energy systems control. He has coauthored several papers on these topics. He can be contacted at email: magri_mounaim@yahoo.fr.

Rachid Lajouad received the Aggregation of Electrical Engineering from the ENSET, Rabat, Morocco, in 2000. The Ph.D. degree in control engineering from theUniversité de Mohammed V, Rabat, Morocco, in 2016, under the supervision of Prof. F. Giri Profand.F.Z. Chaoui. Currently, he is Assistant Professor at the Ecole Normale Supérieure d'Enseignement Technique (ENSET), Hassan II university, Mohammedia, Morocco. His research interests include optimization, observation and nonlinear control of AC machines and energy systems. He has coauthored several papers on these topics. He can be contacted at email: rlajouad@gmail.com.