EEG - Electroencephalogram

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***Abstract*—This project aimed to develop an effective method for analyzing EEG biosignals, focusing on the analysis of brain electrical activity through EEG, emphasizing the importance of different frequency bands (Delta, Theta, Alpha, Beta, and Gamma) and their significance in brain science. Using Fast Fourier Transform (FFT) and various filters, we processed EEG signals to eliminate noise and artifacts, enhancing the quality of the data. We designed and tested both digital and analog circuits using LabVIEW, implementing Low-Pass, High-Pass, Band-Stop, and Band-Pass filters to isolate relevant EEG frequencies. Our results demonstrated that our alternative circuit design, which required fewer materials, provided nearly identical results compared to the more complex setup.**

1. Introduction

In the context of the course of 'Instrumentação Biomédica', we had the opportunity to reassemble several pieces of information that we acquired along our academic journey, which allowed us to develop a project with the main focus on building a way to analyse biosignals using a multitude of tools that were available in the I008 laboratory at FEUP.

The analysis of brain electrical activity is one of the main areas of interest in brain science. As a result, the electroencephalogram (EEG) is important to analyze brain science and is often used in various brain-related research domains [1].

2. EEG Frequency Bands

EEG waveform have several kinds of rhythms, that can be differentiated into five frequency bands, as can be seen in Table 1.

TABLE 1: Frequency range of the EEG signal [2]

Band	Frequency (Hz)
Delta	0.5 to 4
Theta	4 to 7
Alpha	8 to 12
Beta	13 to 30
Gamma	30 to 80

Delta waves (0.5 - 4 Hz) are the slowest EEG waves, normally detected during the deep and unconscious sleep. Theta waves (4 - 8 Hz) are observed during some states of sleep and quiet focus. Alpha band (8 - 14 Hz) originates during periods of relaxation with eyes closed but still awake. Beta band (14 - 30 Hz) originates during normal consciousness and active concentration. Finally, Gamma waves (over 30Hz) are known to have stronger electrical signals in response to visual stimulation [3]. The bands above mentioned can be seen in the following representation:

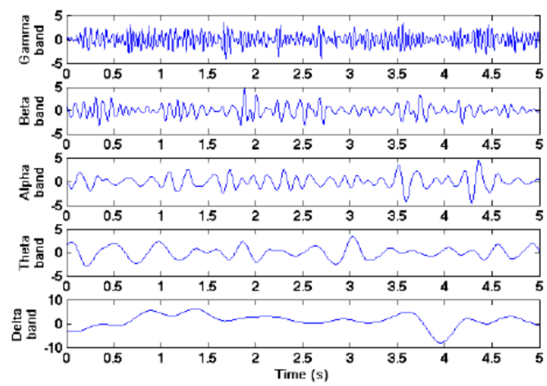

Figure 1: Five frequency bands of EEG signal [3]

3. Fast Fourier Transform

Fast Fourier Transform (FFT) is an algorithm that implements the Fourier transformation, and it is applied to the system to transform signals from the time domain to the frequency domain. It has been presented in studies as a promising tool for stationary signal processing, specifically appropriate for sine waveform such as in EEG signals [4], [5]. We applied this transform to the signal so that we could visualize the energy distribution across different frequency bands, as shown in Figures 4, 18, 22, 25, 28 and 32.

4. Methods

In this project, we used several tools to process EEG signals, such as Labview and a breadboard for constructing analog filters. EEG signals primarily consist of neuronal information below 100 Hz, with most applications focusing on frequencies under 30 Hz [6].

EEG signal processing employs various filters to remove unwanted frequency components, often caused by noise or artifacts. Each filter type is designed to enhance the quality and usability of the EEG data. We used various filters of different types to achieve the desired processing of the EEG signal.

A Low-Pass Filter was set to a cutoff frequency of 40 Hz to attenuate high-frequencies noise and artifacts that typically do not belong to EEG signals of interest. Such high frequencies may include muscle artifacts, high-frequency electronic noise, and electromyography (EMG) signals. Notably, EMG signals are prominent around 200 Hz, as evidenced by their FFT spectrum, as seen in Figure 3.

Following this, a High-Pass Filter with a 1 Hz cutoff was used to eliminate very low frequency drift and DC components from the EEG data. These frequencies are generally caused by slow electrode movement and changes in electrode-skin contact impedance and usually do not contain relevant EEG signal information.

Then, we implemented a Band-Stop filter with a stop band of 49.8 to 50.2 Hz to specifically target line frequency noise, a common interference in EEG recordings due to electrical power lines. This filter effectively reduces electrical interference without significantly affecting other frequencies in the EEG signal. The use of a Band-Stop filter with a narrow stop band could alternatively be achieved using a Notch filter. However, implementing a Notch filter would require additional laboratory materials. Moreover, LabVIEW does not directly support Notch filters, making it more practical to use a Band-Stop filter for this application [7].

Each of these filters helps in cleaning the EEG data by removing different types of unwanted signals and noise, making the resultant EEG signal more suitable for further analysis and interpretation.

To isolate the distinct EEG waveforms, we applied five band-pass filters in LabVIEW, each tuned to specific frequency bands, specified in Table 1.

4.1. Amplification

Human skin exhibits high electrical impedance, typically ranging from tens of kΩ to 1 MΩ, so the instrumental amplifier in the pre-amplification circuit requires much higher input impedance to avoid attenuation of the EEG signal. The first stage of the amplification circuit consists of an instrumentation amplifier AD620AN, that is low cost and it has high accuracy. As it is low powered it is very suitable for medical instrumentation application and uses low power consumption (1.5mW at 3V), which makes it good for portable design [8]. For our project, we amplified the signal by 10 000 times, that by the formula available on the amplifier's data sheet [8] results in a gain resistor with the value of, approximately, 4,7 Ω. The amplification is clear in Figure 5. The formula to obtain the gain resistor is:

$$G = \left(\frac{49.4\,\mathrm{k}\Omega}{R_G}\right) + 1$$

For the implementation of the Low-Pass and High-Pass filters, we used the LM358P operational-amplifier. The LM358P is a versatile dual operational amplifier widely used in various electronic applications (including the design of Low-Pass and High-Pass filters). One of its primary advantages is its low power consumption, making it ideal for battery-operated devices. Additionally, the LM358P operates with a single power supply, which simplifies circuit design and reduces component count. Its high input impedance and low output impedance make it suitable for signal conditioning, ensuring minimal signal loss and distortion. Moreover, the LM358P's wide bandwidth and stable performance enhance the effectiveness of both Low-Pass and High-Pass filters, allowing for precise frequency selection and signal processing [9].

4.2. Signal Acquisition

The signal acquisition was performed using three electrodes: two positioned on either side of the head above the temples, as shown in Figure 6, and one placed on the mastoid as a reference.

Although our goal was to read electrical signals obtained from electrodes placed at strategic locations on the skull, for them to pass through the filters and into LabVIEW, the acquisition proved difficult, and we were unable to visualise any real signals. To test our approach on a real signal, we searched online and downloaded data from a database available from the University Grenoble-Alpes, in France [10].

4.3. Alternative Solution

By analysing the FFT spectrum of the EEG signal before any filtering in LabVIEW, it is possible to see that after 30 Hz there are no significant frequencies, as seen in Figure 4. Besides, as mentioned above, in many applications the EEG information lies below 30 Hz [6].

With that in mind, we developed an alternative solution to the EEG filtering process where we first implemented a Low-Pass filter with a cutoff frequency of 31 Hz, which would reduce the attenuate the frequencies of the power line noise (50 Hz).

Next, we applied the High-Pass filter with the cutoff frequency of 1 Hz and proceeded with the rest as before, without the use of the Band-Stop filter, as seen clearly in Figures 10 and 12.

4.4. Calculations

4.4.1. Formulas.

Active Low-Pass Filter.

$$f_o = \frac{\omega_o}{2\pi} \quad \omega_o = \frac{1}{\sqrt{R_1 R_2 C_1 C_2}} \quad Q = \frac{\sqrt{R_1 R_2 C_1 C_2}}{C_2(R_1 + R_2)}$$

Active High-Pass Filter.

$$f_o = \frac{\omega_o}{2\pi}; \quad \omega_o = \frac{1}{\sqrt{R_1 R_2 C_1 C_2}}; \quad Q = \frac{\sqrt{R_1 R_2 C_1 C_2}}{R_1(C_1 + C_2)}$$

4.4.2. Low-Pass with cut-off frequency of 40Hz.

$$Q = 0.707 \quad R_1 = R_2 \quad C_2 = 0.1\,\mu\text{F}$$

$$0.707 = \frac{\frac{1}{40\times 2\pi}}{0.1 \times 10^{-6} \times 2 \times R_2}$$

$$\iff 0.707 = \frac{1}{40 \times 2\pi \times 0.1 \times 10^{-6} \times 2 \times R_1}$$

$$\iff R_1 \approx 28.1\,\text{k}\Omega$$

$$40 \times 2\pi = \frac{1}{\sqrt{3.63 \times 10^4 \times 3.63 \times 10^4 \times C_1 \times 0.1 \times 10^{-6}}}$$

$$\iff C_1 \approx 200\,\text{nF}$$

4.4.3. High-Pass with cut-off frequency of 1Hz.

$$Q = 0.707 \quad C_1 = C_2 \quad R_1 = 11.3\,\text{k}\Omega$$

$$0.707 = \frac{\frac{1}{1\times 2\pi}}{0.1 \times 10^{3} \times 2 \times C_1}$$

$$\iff C_1 \approx 8.2\text{nF}$$

$$0.707 = \frac{\sqrt{11.3 \times 10^3 \times R_2 \times 1.423 \times 10^{-6} \times 1.423 \times 10^{-6}}}{11.3 \times 10^3 \times (2 \times 1.423 \times 10^{-6})}$$

$$\iff R_2 \approx 22.6\,\text{k}\Omega$$

4.4.4. Low-Pass with cut-off frequency of 31Hz.

$$Q = 0.707 \quad R_1 = R_2 \quad C_2 = 0.1\,\mu\text{F}$$

$$0.707 = \frac{\frac{1}{31\times 2\pi}}{0.1 \times 10^{-6} \times 2 \times R_2}$$

$$\iff 0.707 = \frac{1}{31 \times 2\pi \times 0.1 \times 10^{-6} \times 2 \times R_1}$$

$$\iff R_1 \approx 36.3\,\text{k}\Omega$$

$$31 \times 2\pi = \frac{1}{\sqrt{3.63 \times 10^4 \times 3.63 \times 10^4 \times C_1 \times 0.1 \times 10^{-6}}}$$

$$\iff C_1 \approx 200\,\text{nF}$$

4.5. Labview

LabVIEW played a crucial role in the development of this project, allowing us to test various versions and possibilities. We implemented four different approaches in LabVIEW, each incorporating the two solutions we devised.

Initially, we utilized LabVIEW to capture signals from electrodes post-analog filtering via a Data Acquisition (DAQ) System. Subsequently, we developed a completely digital version of the setup using digital filters and functions. To assess real signals from the database, we crafted an additional fully digital filter and application version. Additionally, we engineered a setup enabling the database signal passage through analog filters on the breadboard before LabVIEW processing.

All information related to functions, controls, indicators, and usage was obtained using LabVIEW Help. [11].

4.5.1. LabVIEW for the signal acquired from the electrodes. For both solution, since the signal was obtained from the electrodes, the LabVIEW setups consisted of a function to acquire the signal that already passed through the analog filters and the DAQ System. The only difference was the application of a Band-Stop filter after the signal acquisition in the solution that utilized it. The rest of the process is the same with the division of the EEG in its bands (specified in Table 1) and the FFT Spectrum analysis of the signal, as shown in Figures 7 and 8.

4.5.2. Digital Simulation. For both alternatives, we did an all digital option with a simulated EEG from LabVIEW, with the respective digital filters, as shown in Figures 9 and 10.

4.5.3. Digital Analysis of a real signal from a database. To evaluate the applicability of our simulated filters discussed in Subsubsection 4.5.2, we used the raw EEG database mentioned in Subsection 4.2. We created a LabVIEW setup aimed at analyzing this signal using all digital filters, as seen in Figures 11 and 12.

4.5.4. Digital and Analog Analysis of a real signal from a database. Furthermore, we also devised an alternative version of the LabVIEW setup, where the database signal traverses the analog circuit via the DAQ System before returning to LabVIEW, implemented for both solutions, as seen in Figures 13 and 14.

4.6. Analog Circuit

The values of the components used on the circuit were based on the calculations above in Subsection 4.4. The components used have values that are the closest to those obtained by calculations, according to the materials available in the laboratory. The circuit can be seen on Figure 2.

This assembly includes, from left to right the instrumentation amplifier, along with a Low-Pass filter with a cutoff frequency of 40 Hz and a High-Pass filter with a cutoff frequency of 1 Hz. Additionally, there's also a Low-Pass filter with a cutoff frequency of 31 Hz followed by another High-Pass filter with a cutoff frequency of 1 Hz. Depending on the connections between the instrumentation amplifier and one of the Low-Pass filters, it is possible to obtain both solution to our project, being the one on the right, the alternative solution. The values used as the basis of calculations were the same ones we used for ECG, given that they are also appropriate for EEG. The voltage used to supplied the circuit was $\pm 9V$.

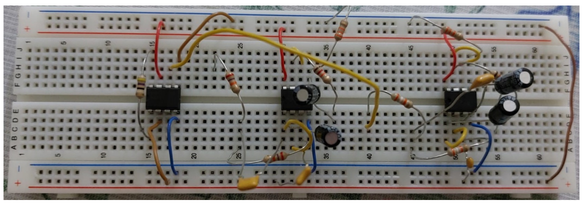

Figure 2: Analog circuit

5. Results

We successfully managed to filter the EEG signals, the simulated by LabVIEW and the one obtained online, separating them into the different EEG bands (visible in Figures 17, 21, 27 and 31). By using the above mentioned combination of amplifiers and filters, we amplified the signal, we eliminated very low-frequency drift and DC components from the EEG data and attenuated high-frequency noise and artifacts that typically do not belong to EEG signals of interest. Additionally, the 50 Hz frequency associated with electrical line interference was also successfully attenuated in both filtering approaches, although more evidently in the approach where we used the Low-Pass Filter with a cutoff frequency of 40Hz, followed by the High-Pass filter with a cutoff frequency of 1 Hz, ending with the Band-Stop Filter. This is notable comparing Figure 28 with Figure 32.

Overall, by comparing the results from the two different approaches (Figure 27 and Figure 31), the difference in the results is not significant, which shows that only using two filters was indeed able to achieve similar results compared to using three filters. The advantage of this approach is the possibility of using fewer materials while providing almost identical results demonstrating efficiency and effectiveness in filtering EEG signals.

Applying the signals both through LabVIEW, in a completely digital versions of our project, as well as through the analog and digital versions, it demonstrated good results, and the waves visualized are clearly EEG waves. The FFT of the signals also represents the spectrum of an EEG signal.

6. Conclusion

This project successfully demonstrated a comprehensive approach to EEG signal processing through the design and implementation of a series of filters, facilitated by the use of LabVIEW and analog circuit design. We effectively analyzed EEG signals by isolating the crucial frequency bands that represent different brain activities, emphasizing the role of the studied waves in brain science.

Our methodology employed both digital and analog processing techniques to enhance the quality of EEG data, with particular attention paid to noise and artifact removal. The use of Fast Fourier Transform (FFT) allowed us to convert time domain signals into their frequency domain counterparts, enabling us to accurately assess the impact of various filters on the EEG signals.

In summary, the assignment was not only successful in the regard that we were able to create a circuit design that efficiently filters and separates the EEG bands, allowing the signal to be analyzed and studied for various diagnostic and research purposes, but also in the sense that we became significantly more acquainted with EEG signals. We learned how to effectively isolate and analyze these bands to glean insights into brain activity, which is essential for diagnosing neurological conditions, studying cognitive processes and developing brain-computer interfaces. This hands-on experience has enhanced our technical skills and knowledge, reinforcing the practical applications and theoretical foundations of biomedical instrumentation.

References

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[11] "Help Menu - NI." [Online]. Available: https://www.ni.com/docs

Appendix

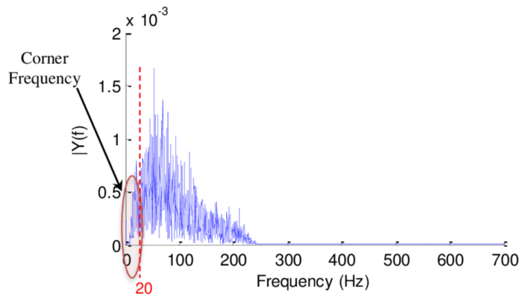

Figure 3: FFT Spectrum of EMG

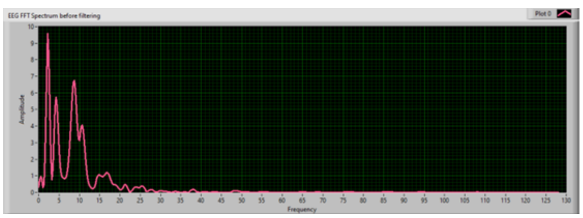

Figure 4: EEG FFT Spectrum before Filtering

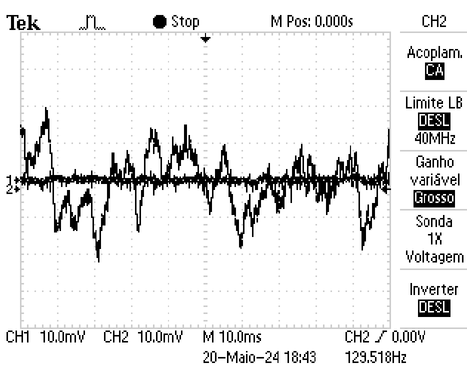

Figure 5: EEG amplification of 10000

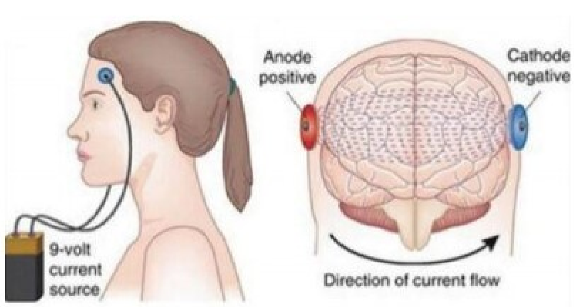

Figure 6: Electrodes' Position

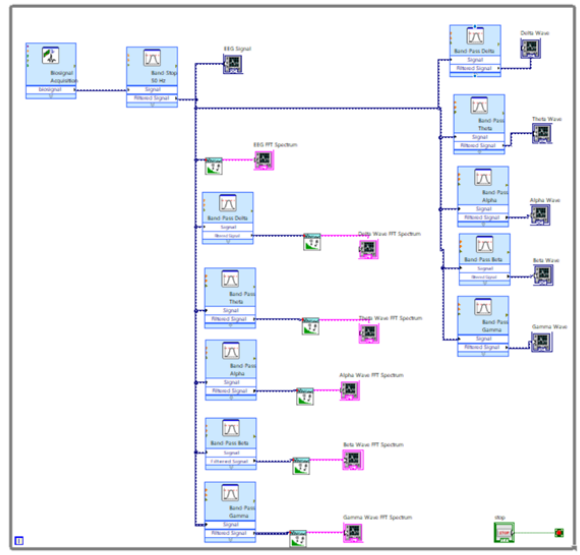

Figure 7: LabVIEW for the signal acquired from the electrodes

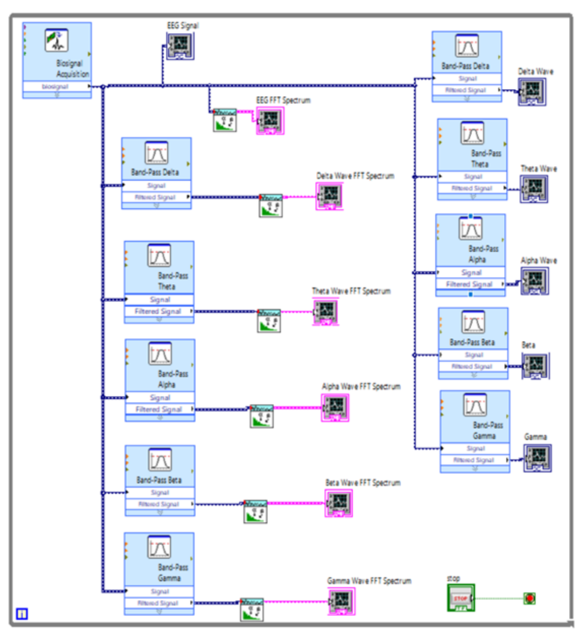

Figure 8: LabVIEW for the signal acquired from the electrodes - Alternative Solution

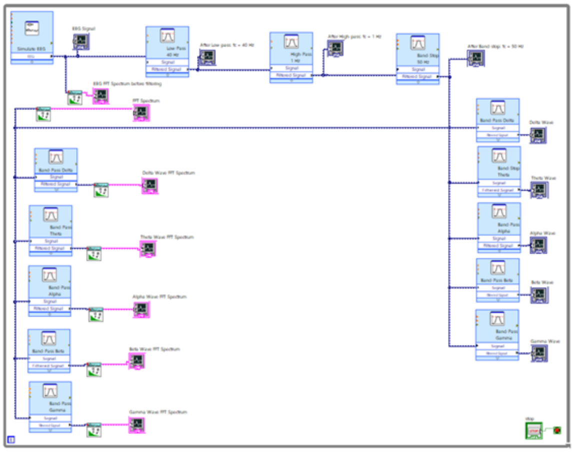

Figure 9: LabVIEW with digital filters

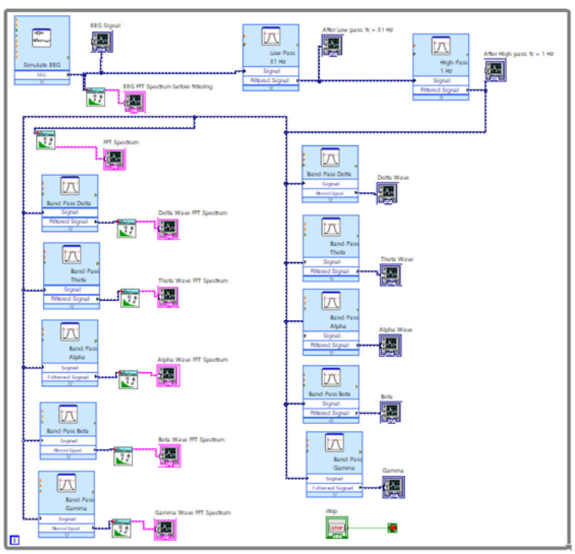

Figure 10: LabVIEW with digital filters - Alternative Solution

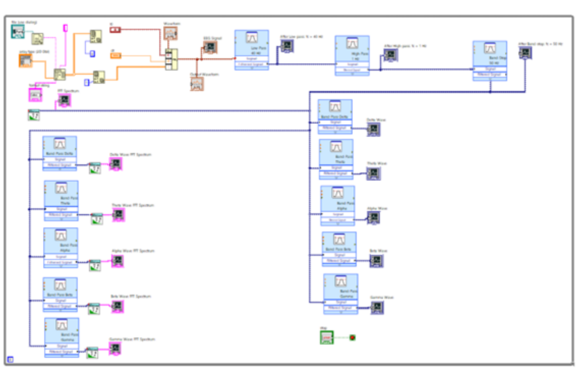

Figure 11: LabVIEW for Digital Analysis of a real signal from a database

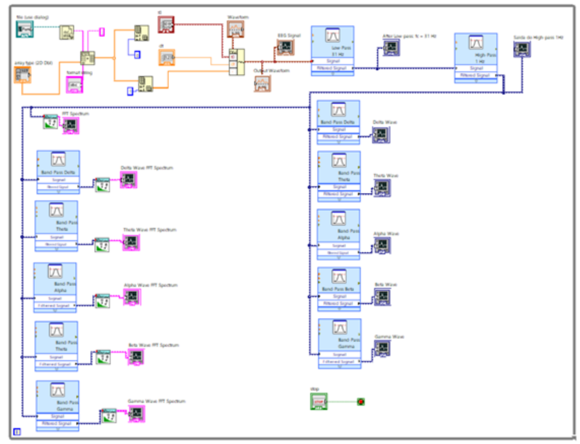

Figure 12: LabVIEW for Digital Analysis of a real signal from a database - Alternative Solution

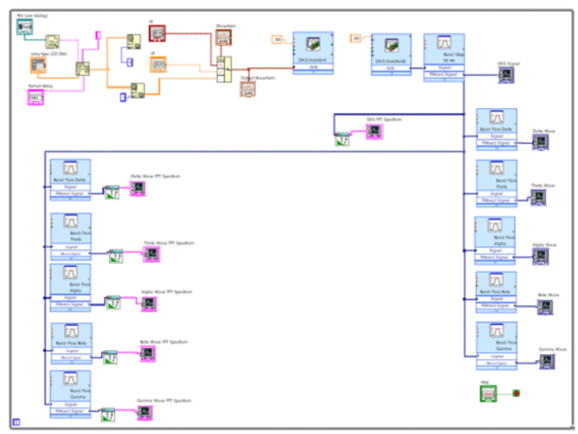

Figure 13: LabVIEW for Digital and Analog Analysis of a real signal from a database

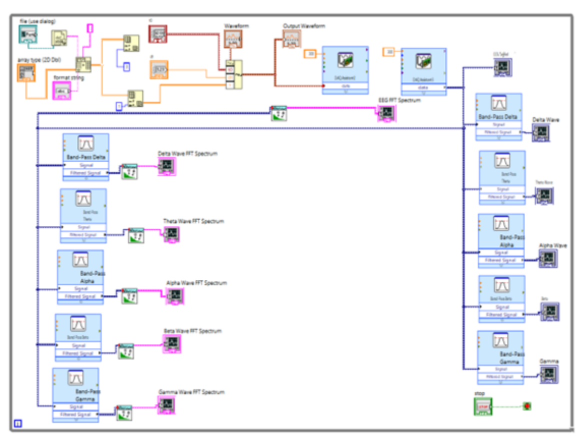

Figure 14: LabVIEW Digital and Analog Analysis of a real signal from a database - Alternative Solution

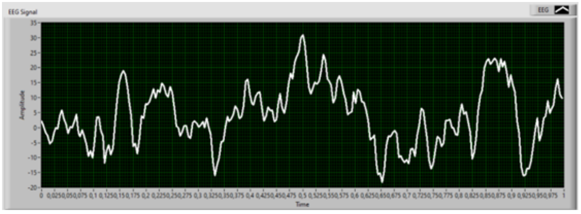

Figure 15: LabVIEW Simulated EEG Signal

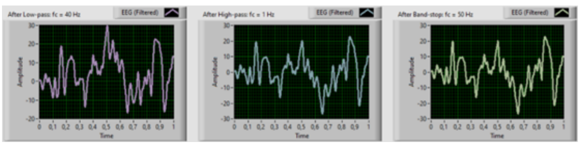

Figure 16: LabVIEW Simulated EEG Signal After Filtering: Low-Pass filter with cutoff frequency of 40 Hz, High-Pass Filter with cutoff frequency of 1 Hz and Band-Stop filter with cutoff band from 49.8 to 50.2 Hz, from left to right

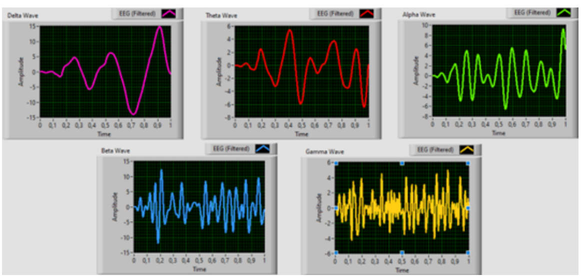

Figure 17: LabVIEW Simulated EEG Signal frequency bands: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

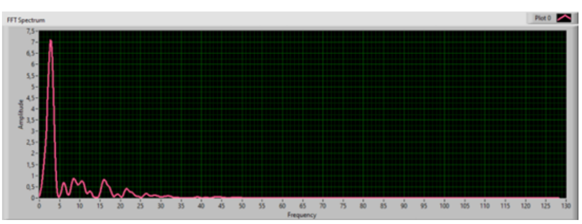

Figure 18: LabVIEW Simulated EEG Signal's FFT Spectrum after filtering

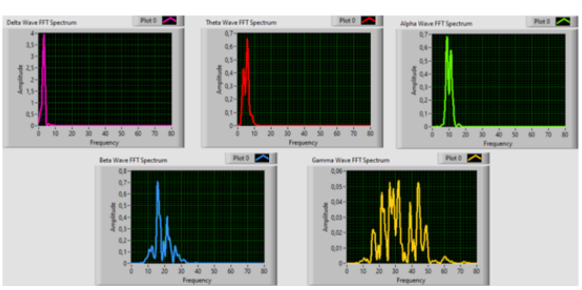

Figure 19: LabVIEW Simulated EEG Signal frequency bands' FFT Spectrum: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

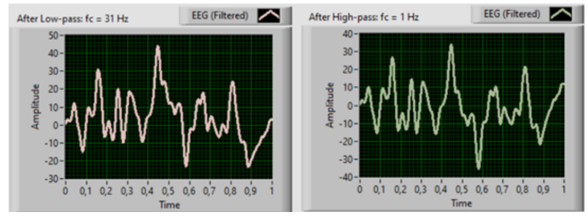

Figure 20: LabVIEW Simulated EEG Signal After Filtering - Alternative Solution: Low-Pass filter with cutoff frequency of 31 Hz and High-Pass Filter with cutoff frequency of 1 Hz, from left to right

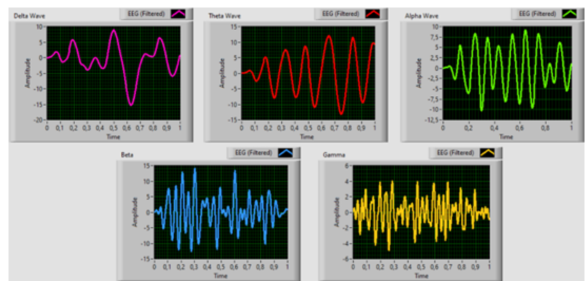

Figure 21: LabVIEW Simulated EEG Signal frequency bands - Alternative Solution: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

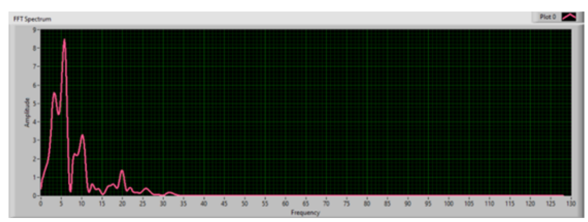

Figure 22: LabVIEW Simulated EEG Signal's FFT Spectrum after filtering - Alternative Solution

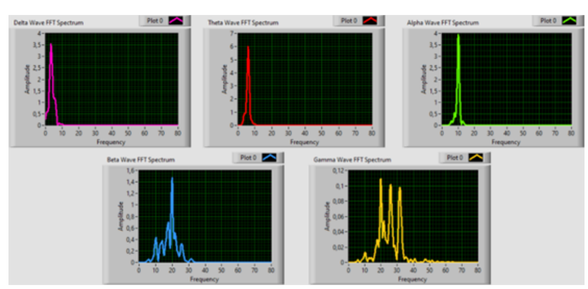

Figure 23: LabVIEW Simulated EEG Signal frequency bands' FFT Spectrum - Alternative Solution: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

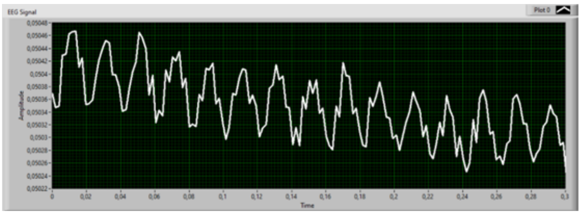

Figure 24: Database EEG Signal

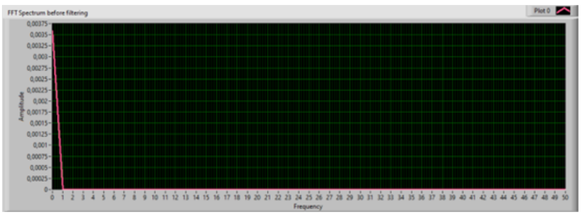

Figure 25: Database EEG Signal's FFT Spectrum before filtering

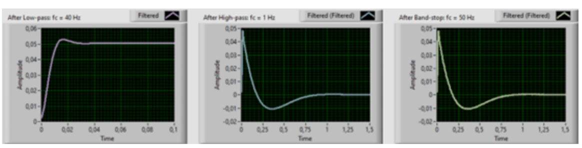

Figure 26: Database EEG Signal After Filtering: Low-Pass filter with cutoff frequency of 40 Hz, High-Pass Filter with cutoff frequency of 1 Hz and Band-Stop filter with cutoff band from 49.8 to 50.2 Hz, from left to right

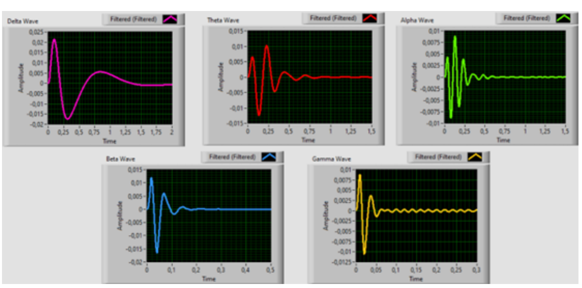

Figure 27: Database EEG Signal frequency bands: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

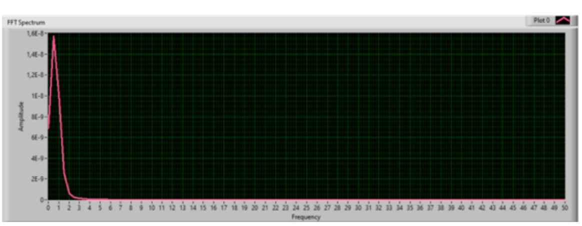

Figure 28: Database EEG Signal's FFT Spectrum after filtering

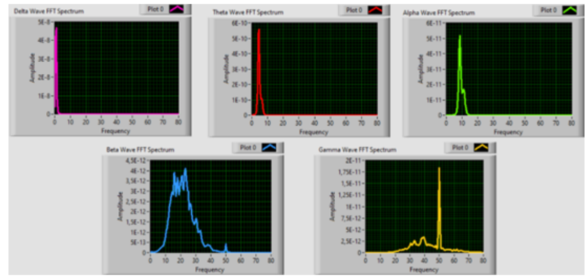

Figure 29: Database EEG Signal frequency bands' FFT Spectrum: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

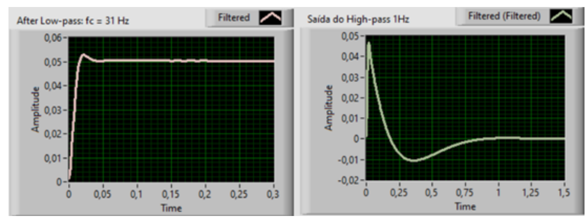

Figure 30: Database EEG Signal After Filtering - Alternative Solution: Low-Pass filter with cutoff frequency of 31 Hz and High-Pass Filter with cutoff frequency of 1 Hz, from left to right

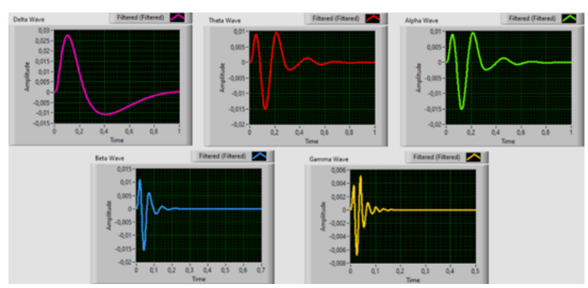

Figure 31: Database EEG Signal frequency bands - Alternative Solution: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom

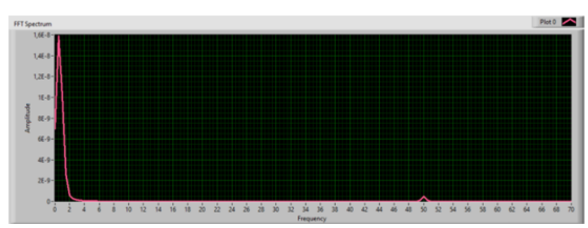

Figure 32: Database EEG Signal's FFT Spectrum after filtering - Alternative Solution

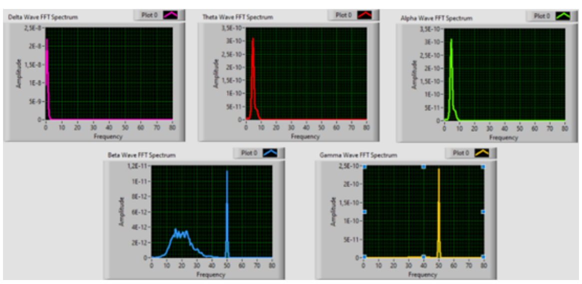

Figure 33: Database EEG Signal frequency bands' FFT Spectrum - Alternative Solution: Delta Wave, Theta Wave, Alpha Wave, Beta Wave and Gamma Wave, from left to right and top to bottom