Green Intelligent Systems and Applications

Research Article
Volume 2(1), 2022, 7-19
https://doi.org/10.53623/gisa.v2i1.65

Finite Impulse Response Filter for Electroencephalogram Waves Detection

Melinda Melinda*, Syahrial, Yunidar, Al Bahri, Muhammad Irhamsyah

Department of Electrical Engineering and Computer, Engineering Faculty, University of Syiah Kuala, Banda Aceh, Indonesia

*Correspondence: melinda@unsyiah.ac.id

SUBMITTED: 23 February 2022; REVISED: 30 March 2022; ACCEPTED: 1 April 2022

ABSTRACT: Electroencephalographic data signals consist of electrical signal activity with several characteristics, such as non-periodic patterns and small voltage amplitudes that can mix with noise making it difficult to recognize. This study uses several types of EEG wave signals, namely Delta, Alpha, Beta, and Gamma. The method we use in this study is the application of an impulse response filter to replace the noise obtained before and after the FIR filter is applied. In addition, we also analyzed the quality of several types of electroencephalographic signal waves by looking at the addition of the signal to noise ratio value. In the end, the results we get after applying the filter, the noise that occurs in some types of waves shows better results.

KEYWORDS: Amplitude, EEG signal, filter; Finite Impulse Respon

1. Introduction

The human brain consists of billions of neurons that play an important role in controlling human behavior, providing internal and external responses to sensory stimuli [1]. The characteristics of the EEG consist of non-destructive side effects and accurate interpretation for several diseases such as epilepsy, memorylessness, Alzheimer's, and autism [2-6]. Several previous researchers have developed various methods to filter EEG signals. One of them is the FIR (Finite Impulse Response) filter. Several previous researchers have carried out FIR filters in EEG signal processing. Research using a low-power filter bank to process EEG signals using the Frequency Response Making (FRM) technique found that the object design was 77% more effective than the FIR filter synthesis technique [7]. Next, research on the Spatial pattern of the Discriminatory General Weight Bank (DSWBCSP) to design FIR to classify EEG signals.The results show that this method can detect and extract bands on brain activity from motor imagery [8]. Then, research on the FIR filter used for denoising by applying the adaptive recursive least square algorithm has been carried out by Vandana [9]. The results show that the proposed technique is more accurate for denoising EEG signals [9]. Brain wave classification and feature extraction techniques by applying Fast Fourier transform have also been carried out by some studies, who successfully filtered the signal using the FIR Butterworth filter [10-13].

This study aimed to suppress noise in several EEG waves so that a clearer visual signal output is obtained and it is easy to analyze further by applying an FIR filter. Then to see the quality of the signal before and after being filtered, SNR (Signal to Noise Ratio) analysis will be carried out on some of these signals so that the quality of the EEG signal can be analyzed.

Furthermore, the EEG signal filtering results are transformed using Fast Fourier Transform (FFT) to change the time domain obtained from the filter results into a frequency domain for analysis.

2. Materials and Methods

The dataset used in this study is brain signal data (EEG) downloaded from https://www.mathworks.com/matlabcentral/fileexchange/55112-eeg-analysis-and-classification. The input signals used in this study are EEG Delta signals in humans during deep sleep, EEG Alpha when relaxed, EEG Beta when thinking is active, and EEG Gamma when panic or fear. We use a Finite Impulse Response (FIR) filter for processing noise suppression and a programming language in the form of a MATLAB 9.1 script. The research method that we propose in this study can be seen in Figure 1 and described later.

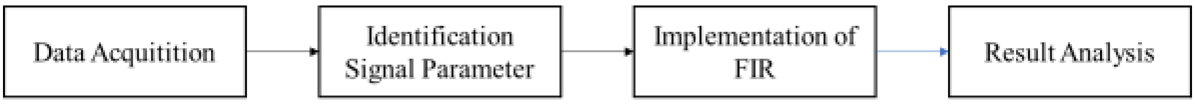

Figure 1. The flow chart of research Method.

2.1. Data Acquisition

EEG signal selection focuses on Delta, Alpha, Beta, and Gamma EEG signal waves. The delta waveform has a wave frequency of < 4 Hz with a voltage amplitude of 10 mV. These waves are generated when a person is fast asleep. Next, we use an alpha waveform with a wave frequency ranging from 8-12 Hz with a voltage amplitude of up to 50 V. Alpha waves are produced when a person is relaxing or in the form of a transition between conscious and unconscious states. Then, the beta wave is worth between 13-30 Hz with a voltage amplitude of between 10-20 V. The gamma waveform has a wave frequency between 31-100 Hz. These waves are generated when a person is experiencing very high mental activity such as fear, panic, etc.

2.2. Signal Parameter Identification

In the EEG signal, there is still noise that will interfere with the information from the signal, either because of interference from the activities of the human body itself or interference from the electronic equipment used during the recording process. Noise can also change the shape of the original signal, increase or decrease the amplitude, and slow down the time, and other forms of change can even damage the digital signal. So to reduce it, a filter process is carried out using the Finite Impulse Response filter method (FIR).

2.3. Filter FIR (Finite Impulse Resonse)

FIR filters are filters with no feedback in the equation. This can be an advantage as it makes the FIR filter inherently stable. Another advantage of FIR filters is that they can produce a linear phase. So, if the application requires a linear phase, the decision is simple, FIR filter should be used. The main drawback of digital FIR filters is their time to execute. Since the filter has no feedback, more coefficients are required in the system equation to satisfy the same requirements required in the IIR filter. There is an additional memory requirement for each coefficient and an extra multiplication for the DSP. For demanding systems, the speed and memory requirements for implementing an FIR system can make the system unfeasible[10]. The output is the measured sum of the current and the finite previous input value for a discrete-time FIR filter. The operation is described by the following equation, which defines the output order $y[n]$ in terms of the input order $x[n]$[11]:

$$y[n] = \sum_{i=0}^{N} b_i X[n-i] \tag{1}$$

Where, N is the digital filter length, bi is the impulse filter response / filter coefficient, X[n] is the input signal sample, X[ni] is the input signal sample held in TDL (Tap Delay Line), y[n] is the output digital filters.

Furthermore, MATLAB simulations are carried out to obtain the SNR value of the four EEG signals, namely the SNR value when the signal is mixed with noise and the SNR value of the signal after the filter process. Then a comparison analysis of the results is carried out on the SNR value. The graph is displayed in the form of a Power Spectral Density (PSD) display before the signal is filtered and after the signal is filtered.

2.4. Signal to Noise Ratio (SNR)

Signal to noise ratio (SNR) is a measure that compares the desired signal level with the background noise level. The greater the SNR value obtained, the higher or better the quality of the network on the path so that data can be sent at high speed. This is inversely proportional to attenuation [12].

$$SNR = 10\ log10\ (Signal\ Power / \ Noise\ Power)\ dB \tag{2}$$

One way to separate the original signal from the presence of noise is to normalize the noise by obtaining the signal SNR constant with the following equation:

$$c = \sqrt{\frac{\sum_{n=1}^{N} s^2(n)}{\sum_{n=1}^{N} b^2(n)}} \tag{3}$$

C is the SNR normalization constant, s(n) is the original signal and b(n) is the noise signal.

Meanwhile, for noise normalization using the following equation:

$$y(n) = s(n) + c.10^{-\frac{SNR}{20}} b(n) \tag{4}$$

Where, y(n) is the noise normalization, c is the SNR normalization constant, s(n) is the original signal and b(n) : the noise signal.

2.5. Simulation of Filter FIR

At this stage, a simulation of the filtering process using the FIR filter method will be carried out on the EEG Alpha, Beta, Delta and Gamma signal datasets. The schematic of the FIR filter simulation can be seen in Figure 2.

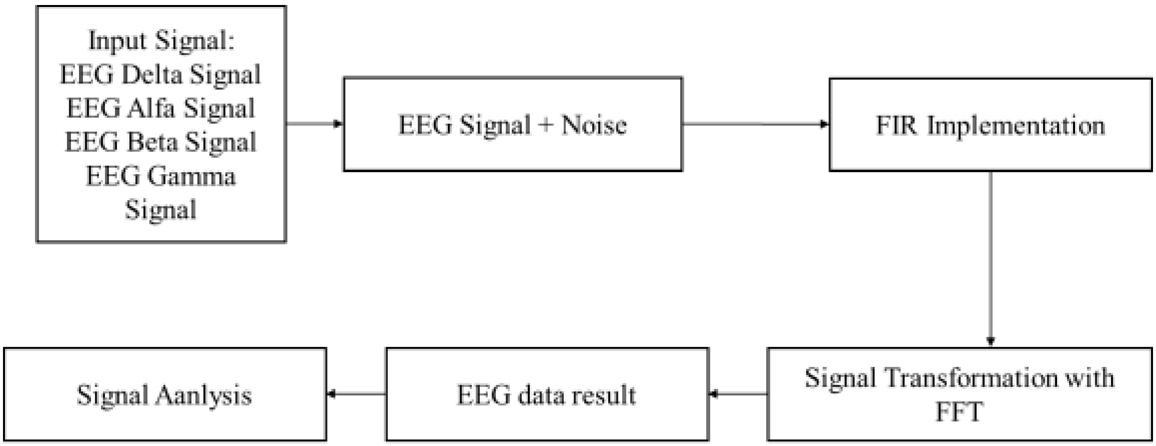

Figure 2. Simulation Scheme of Filter FIR

The steps in the MATLAB simulation will be explained as follows: to begin with, we input the EEG signal dataset (delta, alpha, beta, and gamma) in the form of a script into MATLAB. Then, we also input the value of the variables used, such as sampling frequency, sampling period, data size, time, and variance value. Furthermore, we calculate the noise signal, and the formula sums up the original EEG signal plus the noise signal. By entering FIR filter specifications based on frequency limits such as passband frequency, stopband frequency, passband ripple, stopband attenuation, and density factor values. The next step is to calculate the calculation formula for the FIR filter with several parameters and coefficients. After that, we display the graph by displaying the title, the X-axis containing the time, the Y-axis containing the amplitude, and the graph legend. In addition, perform FFT transformation calculations on the original EEG signal and the noise mixed EEG signal after the FIR filter to get the signal results in the frequency domain with the input of the FFT formula whose results are displayed in the graph of the original EEG signal FFT result and the noise mixed EEG signal after the FIR filter. Lastly, the SNR value of the EEG signal will be calculated before and after the filter for all signal types.

2.6. Result Analysis

At this stage, an analysis will be carried out on the results of the MATLAB simulation using an FIR filter on the EEG signal. In the first experimental stage, the EEG delta signal is carried out, where the original MATLAB EEG Delta coding from the dataset is simulated first. The original EEG signal is added with random noise and filtered using FIR filter coding. After the program is run and the results are displayed in a PSD graph, the results are obtained in the frequency domain where the signal has been filtered from noise and is very close to the original Delta signal from the dataset.

3. Results and Discussion

The results and discussion obtained in this study are divided into several sections based on the type of wave used. And also will be analyzed the wave signal before and after filtering with FIR filter. The last part will show the SNR results for the signal before and after filtering. We use the simulation stages as described previously in the previous method section.

3.1. EEG Delta Signal

The first EEG signal tested in this study was a delta wave signal during sleep in humans. This delta EEG signal data in eegdata.mat file format is downloaded from https://www.mathworks.com/matlabcentral/fileexchange/55112-eeg-analysis-and-classification. After coding the original signal entered in MATLAB, a graph of the displayed signal can be seen. In Figure 3, it can be seen the characteristics of the original delta signal output without the addition of noise in the time domain. In the dataset, 16 experimental points show that the scalp was affixed to 16 points on the human scalp during the EEG data collection experiment. However, the graph only shows one experimental point so that the signal wave is visible.

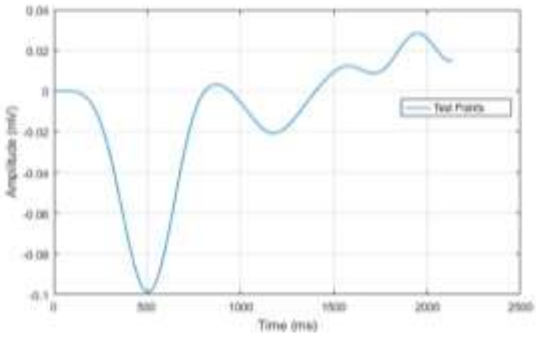

Figure 3. Delta Signal

Figure 3 shows the initial delta wave EEG signal, which is a condition when humans are in a deep sleep, namely in the frequency range of waves that are worth <4 Hz with a voltage amplitude of up to 10 mV. To ensure that the graph output is correct or not, it can be ascertained by performing the FFT transformation and can be seen in Figure 3 the output of the FFT graph in the frequency domain, regarding the number of wave frequencies between 0.5 Hz to 3 Hz and cannot be greater than 4 Hz. according to the characteristics of the delta wave.

3.2. Sum of Delta and Noise EEG Signals

To obtain a delta EEG signal mixed with noise, the delta EEG signal and the noise signal must be added first. In Figure 4, it can be seen the results of the summation of the delta EEG signal and the noise signal where there are shapes that affect the delta EEG signal, where the input noise follows the shape of the original signal.

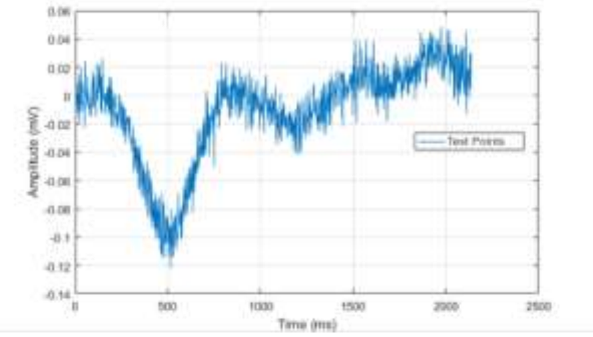

Figure 4. Sum of Delta and Noise EEG Signals

Furthermore, MATLAB simulation adds noise to the original delta wave signal. Based on Figure 4, it can be seen that the signal graph output is very tight. The delta signal has been mixed with noise, and a filtering process is needed to improve signal quality. The addition of noise to the delta signal aims to see the performance capabilities of the Finite Impulse Response (FIR) filter used in this study in suppressing noise.

3.3. Sum of Delta and Noise EEG Signals

At this stage, a simulation is carried out to reduce and suppress noise in the delta signal to which noise has been added using a Finite Impulse Response (FIR) filter, and the results are shown in the following graph.

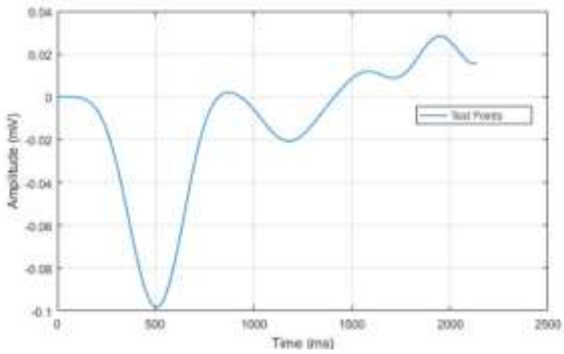

Figure 5. Filter FIR Result of EEG Delta Signal

The delta signal, which was previously mixed with noise, is filtered again to obtain a good signal quality. Where it can be seen in Figure 5, the output of the delta signal after being filtered using an FIR filter is much better when compared to Figure 6 when mixed with noise. After the filter process is carried out to suppress noise, a MATLAB simulation of the transformation process uses the FFT method, which aims to convert the FIR filter results in the time domain into the frequency domain. The results of the graphic simulation can be seen in Figure 6 below.

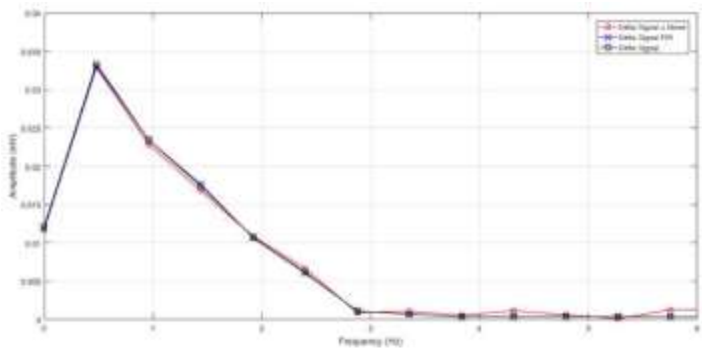

Figure 6. Delta signal FFT transformation before and after filter

Figure 6 shows the results of the transformation of the delta signal mixed with noise and the delta signal mixed with noise after the FIR filter using the FFT method. The FFT process aims to convert the signal from the time domain to the frequency domain to find out the frequency value, which can help to understand the signal characteristics. So that the FFT transformation process is very necessary before the data is analyzed to obtain better EEG signal data. But of course, the results of the delta signal obtained are not the same as the original delta signal, but they are very close.

3.4. Alpha Signal Results After FIR Filter and FFT Transformation

In the next stage, a simulation is carried out to reduce and suppress noise in the alpha signal to which noise has been added using a Finite Impulse Response (FIR) filter, and the results are shown in the following graph.

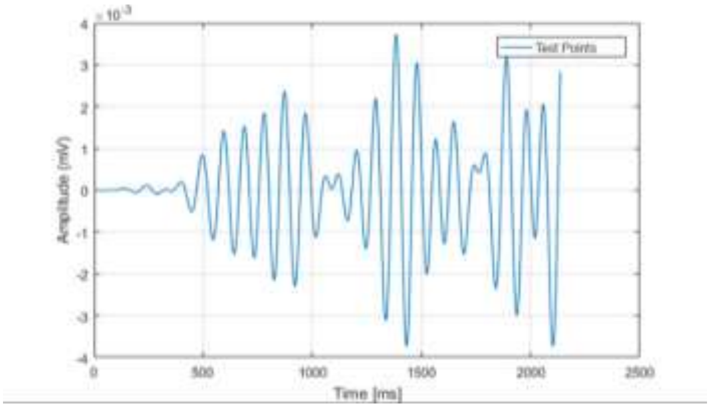

Figure 7. FIR filter results on alpha EEG signal

The alpha signal, previously mixed with noise, was filtered to improve signal quality. It can be seen in Figure 7 that the alpha signal output after being filtered using the FIR filter method is much better than Figure 8 when mixed with noise. After the filter process is carried out to suppress noise, a MATLAB simulation of the transformation process uses the FFT method, which aims to convert the FIR filter results in the time domain into the frequency domain. The results of the graphic simulation can be seen in Figure 8. As highlighted, Figure 8 shows the transformation of the alpha signal mixed with noise and the alpha signal mixed with noise after the FIR filter using the FFT method. The FFT process aims to convert the signal from the time domain to the frequency domain to determine the frequency value obtained to help understand the signal characteristics better. Therefore, the FFT transformation process is necessary to obtain better EEG signal data before the data is analyzed. But of course, the alpha signal results obtained are not the same as the original alpha signal, but they are very close.

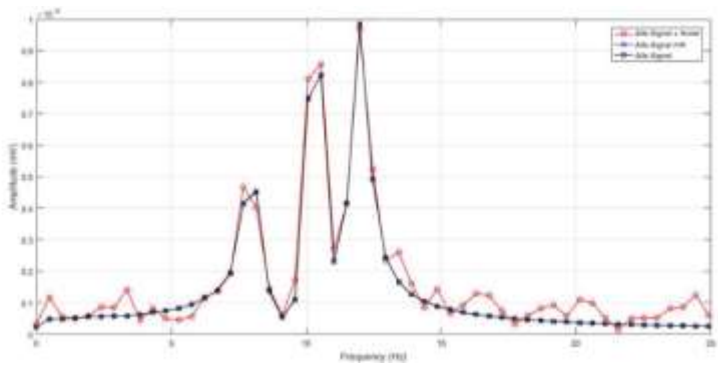

Figure 8. Alpha signal FFT transformation before and after filter

3.5. Beta Signal Result After FIR Filter and FFT Transform

At this stage, a simulation is carried out to reduce and suppress noise in the beta signal to which noise has been added using an FIR filter, and the results are shown in Figure 9.

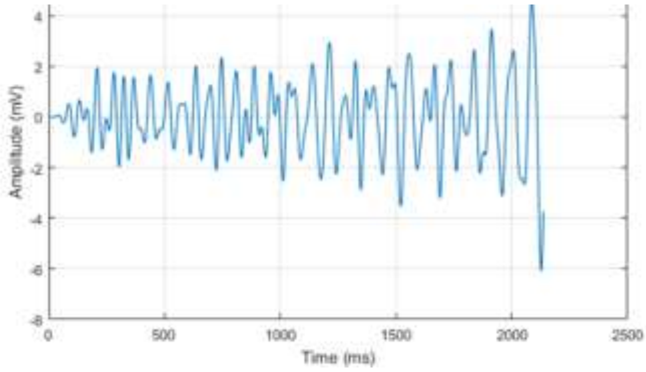

Figure 9. FIR filter results on beta EEG signal

The beta signal, which was previously mixed with noise, was filtered to obtain a good signal quality. As shown in Figure 10, the beta signal output after being filtered using the FIR filter method is much better than Figure 9 when mixed with noise. After the filter process is carried out to suppress noise, a MATLAB simulation of the transformation process uses the FFT method, which aims to convert the FIR filter results in the time domain into the frequency domain. The results of the graphic simulation can be seen in Figure 10.

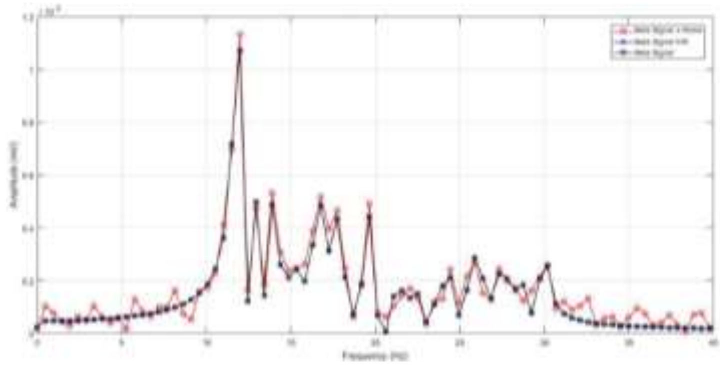

Figure 10. Beta Signal FFT Transformation Before and After Filter

Figure 10 shows the results of the transformation of the beta signal mixed with noise and the beta signal mixed with noise after the FIR filter using the FFT method. The FFT process aims to convert the signal from the time domain to the frequency domain to determine the frequency value obtained to help understand the signal characteristics better. Therefore, the FFT transformation process is necessary to obtain better EEG signal data before the data is analyzed. But of course, the beta signal results obtained are not the same as the original beta signal, but they are very close.

3.6. Gamma Signal Result After FIR Filter and FFT Transform

At this stage, a simulation is carried out to reduce and suppress noise in the gamma signal to which noise has been added using a Finite Impulse Response (FIR) filter, and the results are shown in Figure 11.

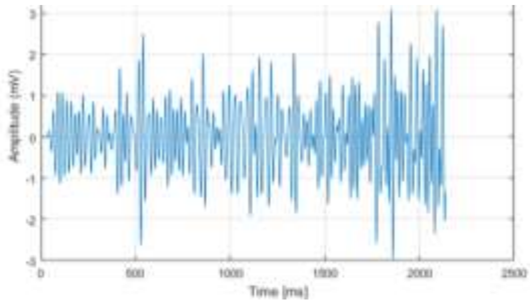

Figure 11. FIR Filter Results on EEG Gamma Signal

The gamma signal, previously mixed with noise, was filtered to obtain a good signal quality. It can be seen in Figure 12 the output of the gamma signal after being filtered using the FIR filter method is much better when compared to Figure 11 when mixed with noise. After the filter process is carried out to suppress noise, a MATLAB simulation of the transformation process uses the FFT method, which aims to convert the FIR filter results in the time domain into the frequency domain. The results of the graphic simulation can be seen in Figure 12.

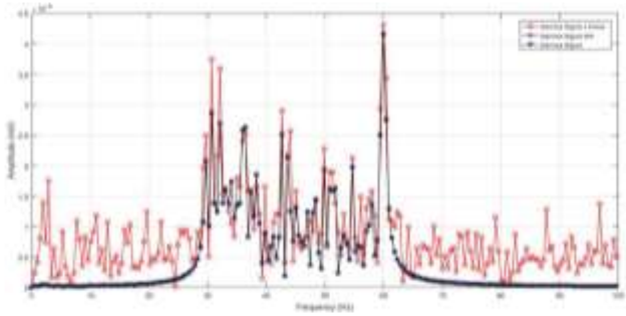

Figure 12. Gamma signal FFT transformation before and after filter

Figure 12 shows the results of the transformation of the gamma signal mixed with noise and the gamma signal mixed with noise after the FIR filter using the FFT method. The FFT process aims to convert the signal from the time domain to the frequency domain to determine the frequency value obtained, thus helping to understand the signal characteristics better. Therefore, the FFT transformation process is necessary to obtain better EEG signal data before the data is analyzed. But of course, the results of the gamma signal obtained are not the same as the original gamma signal, but they are very close.

3.7. Delta Signal Before and After Filtering

Figure 13 shows the EEG Delta input and output signals. Figure 14(a) is a noise-mixed EEG delta signal before filtering, and Figure 14(b) is a noise-mixed EEG Delta signal after filtering, where there are differences in wave height in each period. Before the signal is filtered, the two input signals are summed. The sum of the two signals can be seen in Figure 13(a). The noise seems to interfere with the original EEG Delta signal. After being added up, the signal's shape looks to follow the shape of the original EEG signal. The change in shape is the effect of noise normalization. The initial amplitude in Figure 13(a) ranges from -0.02 - 0.02 mV. Then, Figure 13(b) is the output of the EEG Delta signal mixed with noise after filtering using an FIR filter. In the graph of the output signal, it can be seen that the noise amplitude can be reduced to an amplitude starting from point 0. Besides that, the signal amplitude after filtering becomes larger than the original delta EEG signal. This shows that the noise affecting the original EEG Delta signal before filtering can be suppressed and reduced, and the signal after filtering has a better quality.

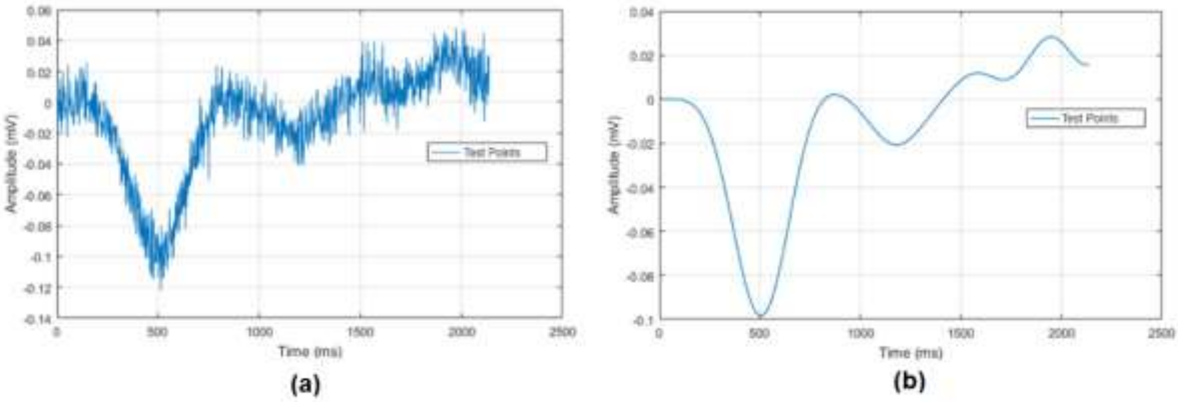

Figure 13. (a) Noise Mixed Delta EEG Signal Before Filtering (b) Noise Mixed Delta EEG Signal After Filtering

3.8. Alpha Signal Before and After Filtering

Figure 14(a) is an alpha mixed noise EEG signal before filtering, and Figure 14 (b) is a noise mixed alpha signal after filtering. Based on the results in Figures 14 (a) and 14(b), the difference in wave height can be seen in each period. Before the signal is filtered, the two input signals are summed the same as for Delta signal processing. Initially, amplitude values ranged from -2.10-3 to 2.10-3 mV. Then the amplitude value fluctuates and has a slightly higher amplitude range than other time ranges, namely -4 to 6 mV at times approaching 1,500 ms. Then, the result of the sum of the two signals can be seen in Figure 14 (a), how the noise seems to interfere with the original EEG Alpha signal. After the summation, the shape of the signals looks like following the shape of the original EEG signal. The change in shape is the effect of noise normalization. Figure 14 (b) is the output of the EEG Alpha signal, which is mixed with noise after filtering with FIR. The output signal graph shows that the noise amplitude can be suppressed to be smaller. Then, the signal starts with an amplitude of 0 mV and is stable until 500 ms. Then the filtered EEG Alpha signal will fluctuate with the up and down of the signal based on the amplitude value, but not as strong as before the fluctuation was filtered. This indicates that the noise affects the original Alpha EEG signal before it is filtered can be suppressed.

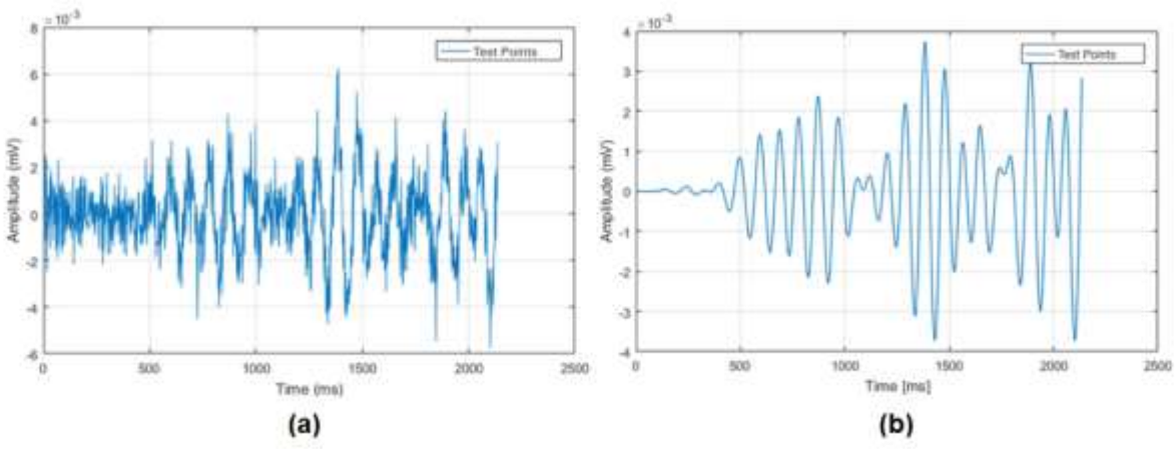

Figure 14. (a) Noise Mixed Alpha EEG Signal Before Filtering (b) Noise Mixed Alpha EEG Signal After Filtering

3.9. Beta Signals Before and After Filtering

Figure 15 describes the EEG Beta input and output signals. Figure 15(a) is a noise-mixed Beta EEG signal before being filtered, and Figure 15(b) is a noise-mixed EEG signal after filtering where there are differences in wave height in each period. Before the signal is filtered, the two input signals are summed. The sum of the two signals can be seen in Figure 15(a). The noise seems to interfere with the original Beta EEG signal starting from the beginning to the end of the beta signal. After being added up, the shape of the signal seems to follow the shape of the original EEG signal. The change in shape is the effect of noise normalization, and there is also a significant signal fluctuation.

Furthermore, Figure 15(b) shows the output of the mixed-noise beta EEG signal after filtering. Based on the graph of the output signal, it can be seen that the noise amplitude can be reduced to a smaller size, and there is no signal fluctuation anymore. The range of signal amplitude values moves up and down slowly and in parallel, starting from a smaller range of -2.10-3 to 2.103 at 0 ms and ending in the range of -6.10-3 to 6.10-3 at 2100 ms. In addition, the amplitude of the signal after filtering becomes larger than the original beta EEG signal. This indicates that the noise affects the original beta EEG signal before filtering.

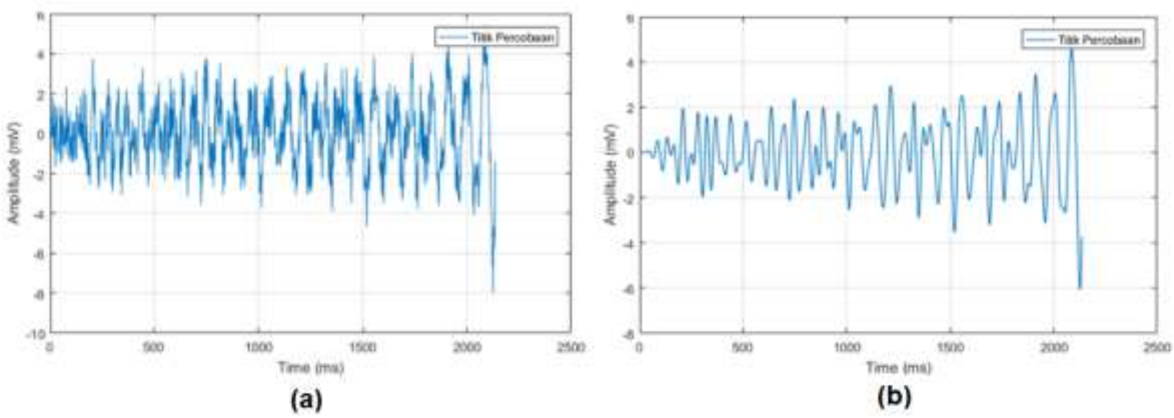

Figure 15. (a) Noise Mixed Beta EEG Signal Before Filtering (b) Noise Mixed Beta EEG Signal After Filtering

3.10. Gamma Signal Before and After Filtering

The display of the EEG Gamma input and output signals can be seen in Figure 16. Figure 16 (a) is a noise-mixed EEG gamma signal before being filtered, and Figure 16 (b) is a noise-mixed EEG gamma signal after being filtered, where there are differences in wave height in each period. Before the signal is filtered, the two input signals are summed. The sum of the two signals can be seen in Figure 7(a). The noise seems to interfere with the original EEG gamma signal. The fluctuation of the gamma signal before being filtered is very significant and has a stable range of amplitude values, namely -3.10-3 to 3.10-3. In addition, the shape of the signals after the summation seems to follow the shape of the original EEG signal. Then, Figure 16(b) is the output of the EEG Gamma signal mixed with noise after filtering. The output signal graph shows that the amplitude of the noise can be reduced to a smaller size, with the initial amplitude range from -10-3 to 10-3. In addition, the amplitude of the signal after filtering becomes larger than the original form of the EEG gamma signal. This shows that the noise affects the original EEG Gamma signal before it is filtered can be minimized.

3.11. Comparison of Signal to Noise Ratio (SNR) Before and After Filtered

The SNR values before and after being filtered can be seen in table 1. Based on the results in the table, it can be seen that the increase in the SNR value for each EEG input signal is different. This increase in SNR value indicates that the ratio of the original EEG signal power is greater than the noise power. So that after filtering using an FIR filter, it can suppress the disturbing noise from the original EEG signal, thereby producing a signal output with better quality.

In addition, the results in table 1 also show that the largest increase in the SNR value is found in the EEG gamma signal, namely when the human condition is panicking or afraid, with an SNR increase of 0.0742 dB. The greater the SNR value in the signal when the signal is mixed with noise, and after being filtered, the results show that the FIR filtering process works very well on the signal. The increase in the SNR value of the input signal is affected by the frequency power density of the noise input signal.

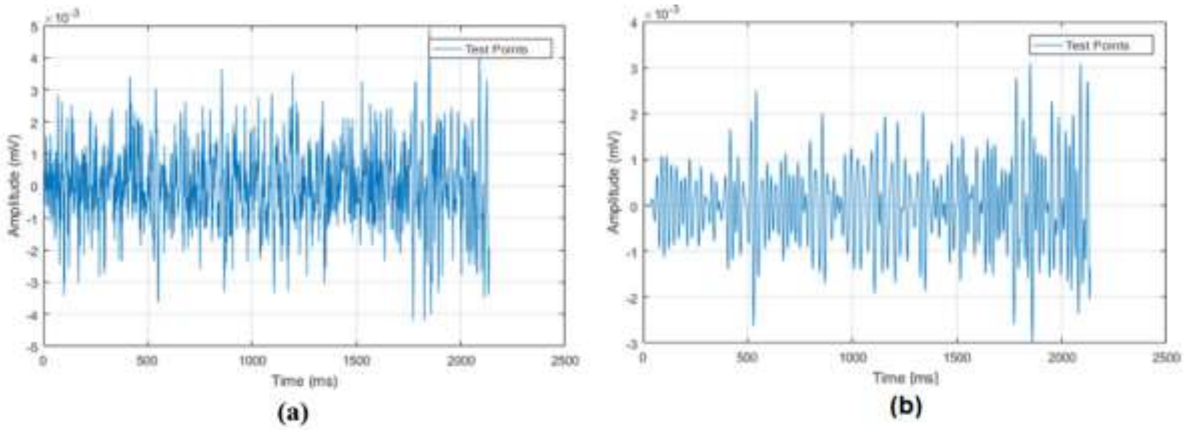

Figure 16. (a) EEG Gamma signal mixed with noise before filtering (b) EEG Gamma signal mixed with noise after filtering

Table 1. Comparison of SNR Values before and after filtering.

EEG Signal	SNR before (dB)	SNR After (dB)	Increase value (dB)
EEG *Delta*	3,1542	3,2198	0,0656
EEG *Alfa*	2,4182	2,4832	0,065
EEG *Beta*	2,6991	2,7696	0,0705
EEG *Gamma*	-1,6756	-1,6014	0,0742

It can be added when the EEG signal is mixed with noise. The EEG Gamma signal has the smallest SNR value of -1.6756 dB, and the largest SNR value is found in the Delta EEG signal of 3.1542 dB. Finally, the largest increase in SNR value between before and after the filtering process was found in the EEG Gamma signal of 0.0742 dB, and the smallest increase in SNR value was found in the EEG Alpha signal of 0.065 dB.

4. Conclusions

This research has been able to apply FIR filters to several EEG wave signals, namely: Delta, Alpha, Beta, and Gamma. Several important points can be concluded from the results obtained. First, the performance results of the Finite Impulse Response (FIR) filter work very well and efficiently in suppressing noise in Delta, Alpha, Beta, and Gamma EEG signals. Then, the largest SNR value before being filtered occurs in the EEG Delta signal and the smallest SNR value in the EEG Gamma signal.

Acknowledgments

I would like to thank LPPM Syiah Kuala University, Banda Aceh Indonesia, for supporting this research and also to all parties involved in it.

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