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Utilization of Adaptive Filters for Artifact Cancellation in Electroencephalography Signals

A thesis submitted in partial satisfaction

of the requirements for the degree Master of Science

in Electrical Engineering

by

Kayvon Sadeghi

2015

ABSTRACT OF THE THESIS

Utilization of Adaptive Filters for Artifact Cancellation

in Electroencephalography Signals

by

Kayvon Sadeghi

Master of Science in Electrical Engineering

University of California, Los Angeles, 2015

Professor Kung Yao, Chair

Electroencephalography (EEG) is a technique that is used to non-invasively monitor the electrical activity of the brain. Although the EEG device is supposed to record only cerebral activity, it also records artifacts, which are recorded activities that are not of cerebral origin. These artifacts include motion artifacts and stimulation artifacts. Artifacts corrupt the EEG signals and prevent the device from being used successfully. In order to remove the artifacts in real-time, an artifact cancellation system that utilizes adaptive filters is proposed. Adaptive filters can self-adjust the transfer function, giving them the ability to self learn and change filter

parameters to adapt to different signal characteristics. Multiple adaptive filter algorithms were tested in the artifact cancellation system in Matlab and Simulink, including Least Mean Squares (LMS) algorithms and Recursive Least Squares (RLS) algorithms. The RLS algorithm has a faster convergence time but is more computationally demanding than the LMS algorithm.

The thesis of Kayvon Sadeghi is approved.

William J. Kaiser

Lei He

Kung Yao, Committee Chair

University of California, Los Angeles

2015

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CHAPTER 1

INTRODUCTION/BACKGROUND

1.1 Neural Recording Systems

Neural recording systems are used to monitor brain activity, and different neural recording systems have varying levels of invasiveness. The level of invasiveness depends on the placement of the electrodes used to detect and measure neurons firing in the brain[1].

1.2 Invasive Systems

In invasive systems, electrodes are inserted directly into the grey matter of the brain during neurosurgery. Invasive systems have several advantages, including excellent signal quality, very good spatial resolution, and a high frequency range. But one of the main disadvantages of the invasive system is that it requires surgery and puts the patient at risk of further complications due to surgery. In addition, since the device is implanted in the brain, it may not provide a safe and stable recording over time due to foreign body reaction.

Foreign body reaction occurs because the electrodes are implanted into the tissue, causing damage to tissues and vessels along the insertion path[2]. This activates immune cells, such as microglia[3]. In addition, astrocytes, which cause scar formation, are recruited and drawn to the damaged site (Figure 1)[4]. Scar formation occurs in order to minimize damage and neural degeneration. Unfortunately, the scar increases the distance between the signal and the interface, which contributes to deteriorating signal quality[5]**.** This is shown in Figure 2**.** There are four stages in this scar formation, including inflammation, astrocytes, neuronal bodies, and neurofilaments. Each of these stages of scar formation increases the distance between the signal and the interface. Because of this, signal quality deteriorates over time.

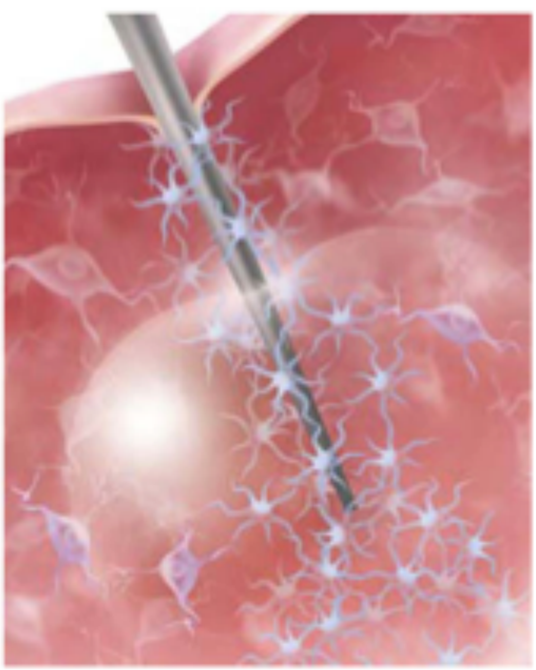

Figure 1: Foreign body reaction

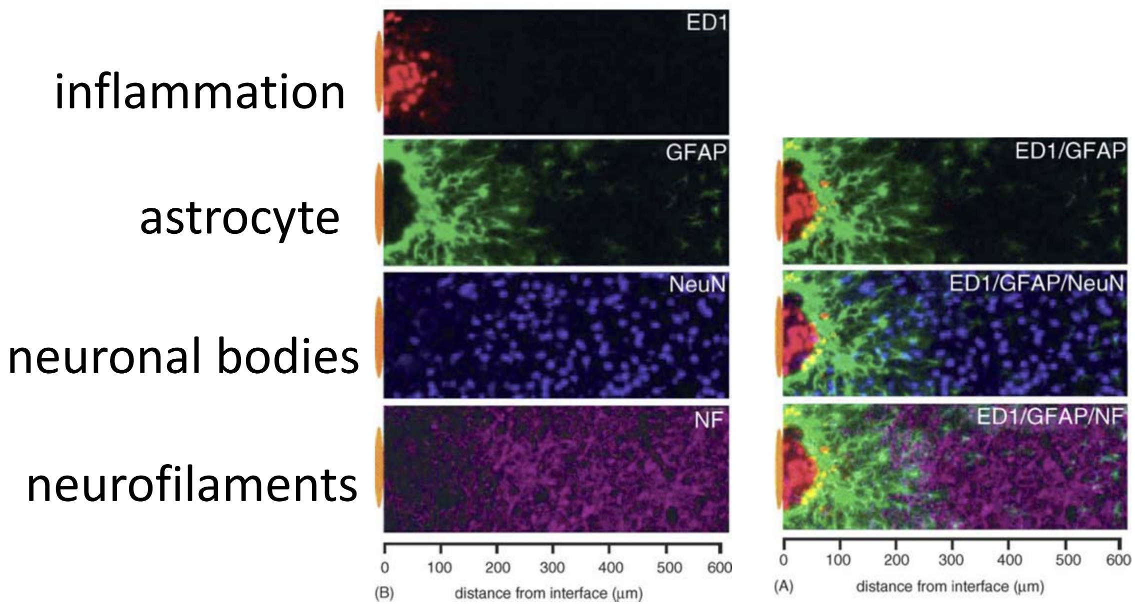

Figure 2: Scar increasing the distance between signal and interface

1.3 Non-Invasive Systems: Electroencephalography

Electroencephalography (EEG) is a technique that is used to non-invasively monitor the electrical activity of the brain by measuring the local potential at the scalp[6]. It used for various applications, including detection of epileptic seizures, which cause abnormally excessive or simultaneous neuronal activity in the brain[7]. A major advantage for non-invasive systems over invasive systems is that there is no need to perform surgery. Non-invasive systems are also inexpensive and lightweight compared to other methods[8]. However, the signal is susceptible to unwanted electrical activity from sources other than cerebral activity, known as artifacts[9].

1.4 Artifacts

It is extremely important that the output signal of the electrical activity is an accurate representation of the actual signal, allowing for a correct reading. But unfortunately, there are sources of noise that limit this technology. Although the EEG is supposed to record only cerebral activity, it can also record artifacts, which are unwanted electrical activities that are not of cerebral origin. This can disturb the recordings, causing the output signal to not be accurate[9]. Due to this corruption of the signal, it stops the EEG from giving an accurate and precise signal that is necessary for its desired applications. There are different types of artifacts, such as motion artifacts, stimulation artifacts, and powerline interference. Motion artifacts and stimulation artifacts are the focus of this project.

1.5 Motion Artifacts

Motion artifacts are one of the largest sources of noise for EEG recordings. They can disturb the recordings, thus lowering the signal quality. This makes interpretation of the signals difficult and may lead to detection of the wrong event or false alarms. Thus, removal of motion artifacts is a significant problem. There has been a lot of research done on motion artifact detection, with different groups investigating various methods[10,11,12,13]. It has been shown in literature that electrode-tissue impedance has a correlation with motion artifacts (Figure 3).[14] Changing the distance between the skin and the electrode or stretching/twisting the skin can change the electrical properties and alter the electrode-tissue impedance, thus causing motion artifacts.[15] Figure 3 shows the potential and impedance change during pressing and stretching, which leads to motion artifacts.

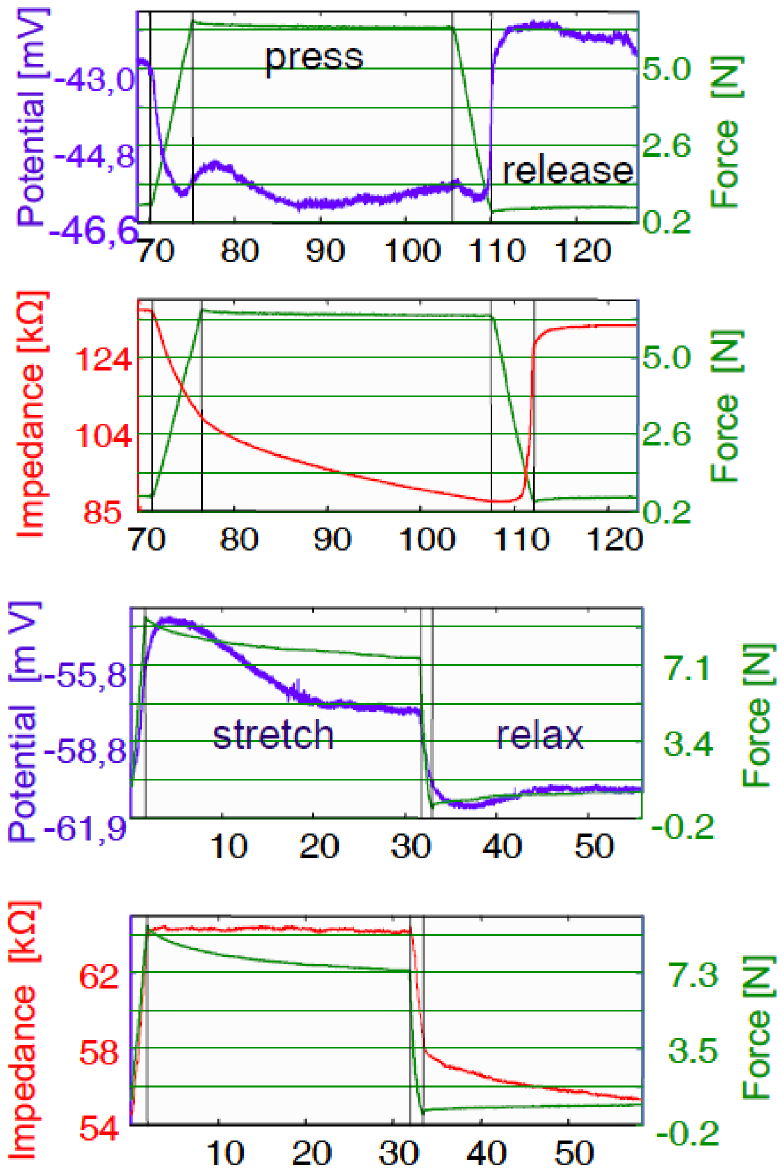

Figure 3: Potential and impedance change due to pressing/stretching

In order to remove the motion artifacts, the electrode-tissue impedance needs to be determined and then used to estimate the motion artifact signal that should be cancelled. Once the motion artifact is estimated, it can be removed from the corrupted signal to get the clean signal.

1.6 Stimulation Artifacts

Stimulation artifacts occur due to stimulation of neural tissues. The stimulation artifacts are due to charge accumulation at the electrode-electrolyte interface that occurs during stimulation[16]. There is a large RC time constant, causing stimulation artifacts to last for extended periods of time and saturate the recording amplifier. These artifacts prevent recording of neural activity since the amplifier is saturated during the stimulation. It is important to be able to record the response of neurons to stimulation, and these stimulation artifacts prevent this from happening. The stimulation artifacts are difficult to filter out since the stimulus shares some qualities with the spikes of the EEG signal. Once the stimulation artifacts are estimated, they can be subtracted from the corrupted signal to get the artifact-free signal.

1.7 Removal of Artifacts

There have been many attempts to remove artifacts using post-processing methods, but artifact cancellation while the signal is occurring is important for many real-time applications. In addition, the original signal may not be recoverable with post-processing methods. In order to remove the artifacts, the artifacts need to be modeled and then removed using filtering techniques, such as adaptive filters. Chapter 2 will cover artifact modeling and Chapter 3 will cover adaptive filters.

CHAPTER 2

MODELING ARTIFACTS

2.1 Motion Artifacts

In order to model motion artifacts, there are a few steps that need to be completed. First, there needs to be an analog front end that can retrieve the EEG signal and the impedance signal from the skin through an electrode, which will allow the motion artifacts to be identified. The device will measure the impedance signal as well as the local field potentials through the electrode. Previously, IMEC has developed an Analog Front End for a similar application with electrocardiograms (ECG).[17] One issue with this device is that its current sources generate a sinusoidal wave, which requires a complex system to obtain the real and imaginary components of the electrode-tissue impedance[15]. An alternative to the method IMEC used is to use a simplified electrode model (Figure 4) and current source that generates a square pulse (Figure 5) [18]. Using this method, use of a more complex system can be avoided.

In Figure 4, R_s is the tissue impedance, C_{dl} is the double layer capacitance, and $Z_{faradaic}$ is the Faradaic impedance. In this case, we can determine the tissue impedance and the capacitance by knowing the pulse width, current amplitude, and voltage, which will then allow calculation of the impedance Z ($Z = \frac{1}{j\omega C}$) as a model for the motion artifact.

Figure 6 shows the corresponding voltage from the current source that generates a square pulse[18]. At (a), there is an IR drop at the electrolyte. At (b), there is a drop due to double layer capacitance, and at (c), there is a drop to due to the Faradaic impedance. Electrolysis occurs at (d).

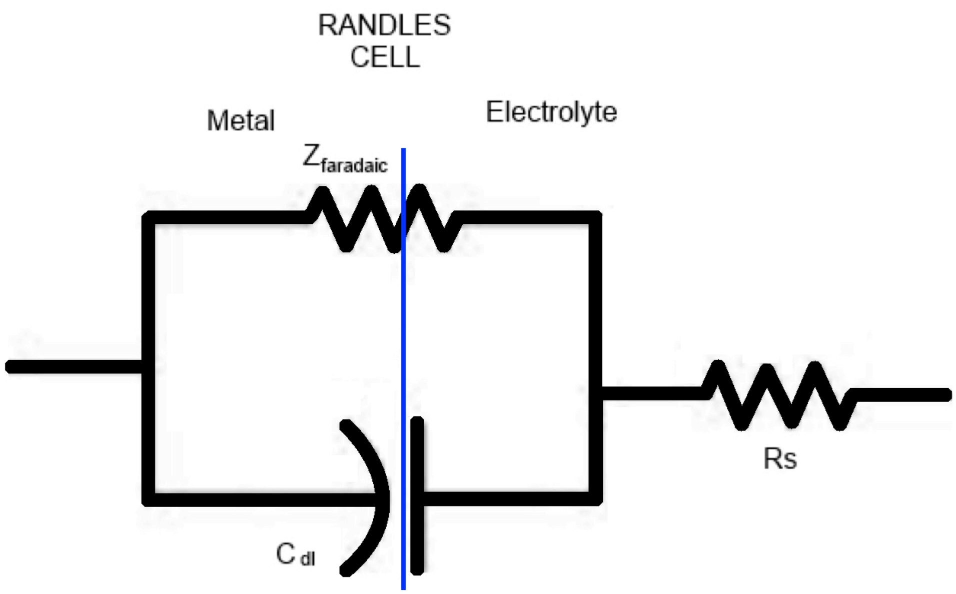

Figure 4: Circuit element model of an electrode (Randles cell)

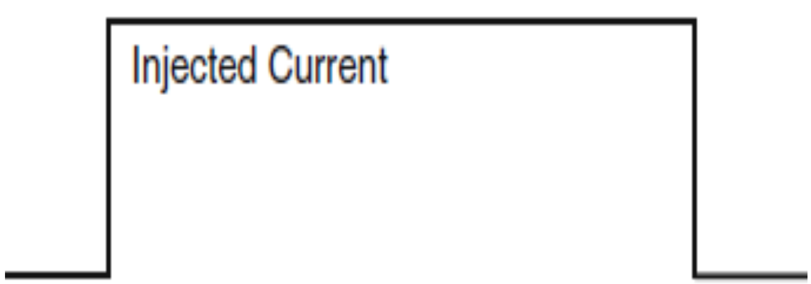

Figure 5: Current pulse used to measure impedance

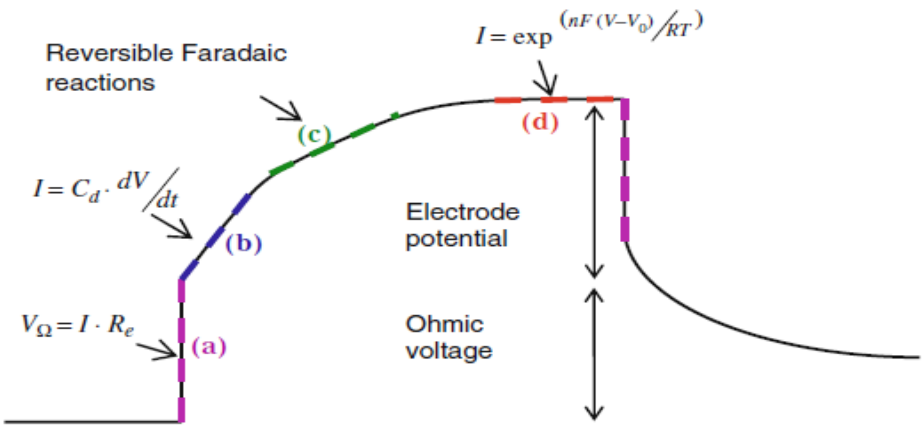

Figure 6: Resulting voltage from current pulse

2.2 Stimulation Artifacts

When the neural tissue is stimulated with the stimulator, stimulation artifacts can occur. To model the stimulation artifacts, the artifacts need to be sampled[18]. To sample the artifact, an amplifier can be used to record the resulting signal when a stimulus is applied.

The signal can be filtered to only include signals above the maximum physiological response. An ADC can be used as this amplitude filter. This is done so only the stimulation artifacts are remaining. This resulting signal is stored, sent through a DAC, and used as a reference signal for the stimulation artifact.

CHAPTER 3

ADAPTIVE FILTERS

3.1 Adaptive Filters

An adaptive filter can self-adjust its transfer function, giving it the ability to self learn and change filter parameters to adapt to different signal characteristics. Although there are both infinite impulse response (IIR) adaptive filters and finite impulse response filters (FIR), FIR adaptive filters are more commonly used[19]. This is because they have better stability and do not require any special modifications in order to be used.

Adaptive filters are used to obtain the desired signal without any undesired noise by reducing the noise that is corrupting the signal. The process is shown in Figure 7 below.[20] There are two inputs for the adaptive filter: x(n) and d(n). The input x(n) is the reference signal, which corresponds to the undesired noise that needs to be filtered out. This reference signal is not exactly the same as the noise corrupting the signal, so it cannot just be removed from the corrupted signal to get the desired signal. The reference signal can have a different phase, amplitude, or time delay than the actual noise signal. The input d(n) is the primary input, which corresponds to the desired signal plus the undesired noise.

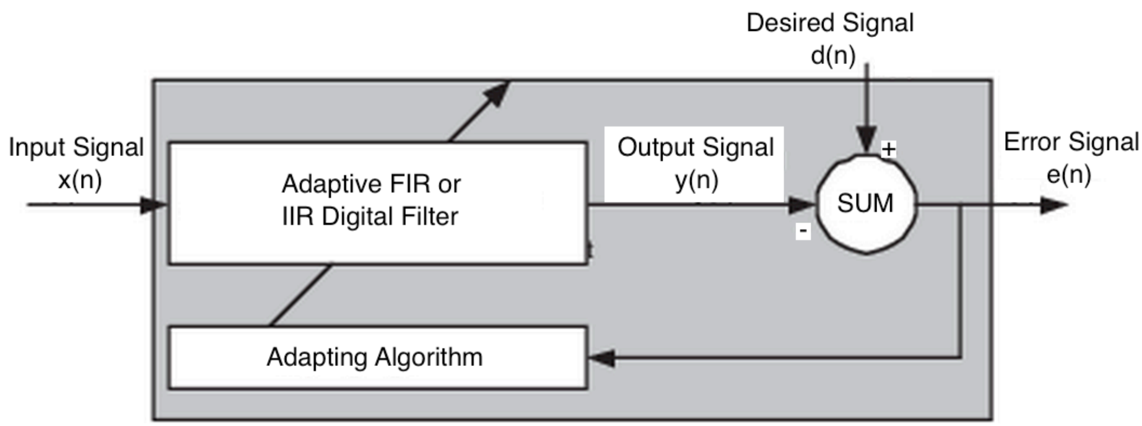

Figure 7: Adaptive filter system

Instead of just subtracting the reference signal from the corrupted signal, the adaptive filter predicts the noise that is present in the corrupted signal and then subtracts it. The reference signal x(n) is used to help make the prediction because it is chosen to be similar to the noise that is corrupting the signal. Also, the reference signal x(n) is filtered in order to account for the phase, amplitude, and time delay. Filtering the reference signal results in y(n), which is the prediction of the noise that is corrupting the signal. Once the reference signal is filtered, it is subtracted from the corrupted signal in order to obtain e(n), which is the error signal. The error signal e(n), which is the difference between d(n) and y(n), is the output of the system. If done correctly, this can be used to recover the desired part of the signal, with the undesired noise filtered out.

3.2 Adaptive Filter Algorithms

When an adaptive filter is used, the relationship between the input and output signals of a filter is iteratively modeled. In this process, the filter coefficients of the adaptive filter are self-adjusted using an adaptive algorithm. The coefficients are adjusted in order to minimize the power of e(n). Multiple adaptive algorithms were researched and tested, and the two most promising adaptive algorithms were the Least Mean Squares (LMS) algorithm and the Recursive Least Squares (RLS) algorithm. The LMS algorithm involves less computationally demanding calculations and is less complex than the RLS algorithm, thus causing the LMS algorithm to need less memory and computational resources than the RLS algorithm[20]. However, the correlation matrix of the input signal for the LMS has a large eigenvalue spread, which can degrade the convergence of the adaptive filter. The RLS algorithm does not have the large eigenvalue spread problem, potentially allowing for a faster convergence speed. The RLS algorithm is more complex than the LMS algorithm but has the potential to perform better in time varying environments.[21]

3.3 Least Mean Squares Algorithm

The LMS algorithm converges on the optimal solution by updating coefficients, also known as filter weights. This optimal solution occurs when the error signal between the desired signal and the output signal is minimized. These coefficients are updated in each iteration in order to get to the optimal solution. To update the coefficients, the LMS algorithm performs three main steps, which include calculating y(n) from the adaptive filter, calculating e(n), and then finally updating the filter coefficients[19,23,24].

In order to calculate y(n), which is the prediction of the noise that is corrupting the signal, the following equation can be used:

$$y(n) = u^T(n)w(n)$$

where $u(n)$ is the filter input vector of time delayed input values

$$u(n) = [x(n)x(n-1)x(n-2) \dots x(n-N+1)]^T$$

and $w(n)$ is the filter coefficients vector at time n

$$w(n) = [w_0(n)w_1(n)w_2(n) \dots w_{N-1}(n)]^T$$

Then e(n), the error signal, is calculated using the following equation:

$$e(n) = d(n) - y(n)$$

Finally, the filter coefficients (filter tap weights) are updated with the following equation:

$$w(n+1) = w(n) + 2\mu e(n)u(n)$$

where $w(n)$ is the filter coefficients vector, $u(n)$ is the filter input vector, and μ is the step size of the adaptive filter (normally a small positive constant). If μ is too large, the adaptive can become unstable and diverge, while if μ is too small, the convergence time to the optimal solution can significantly increase.

3.4. Normalized Least Mean Squares Algorithm

In the LMS algorithm, some values of μ can cause a noise amplification problem. The Normalized Least Mean Square algorithm can solve this problem. In the Standard LMS algorithm, the equation for updating the filter coefficients $w(n+1)$ uses μ, while in the Normalized Least Mean Square algorithm, the equation uses an alternate version of μ:[25]

$$\mu(n) = \frac{\alpha}{c + \| x(n) \|^2}$$

where α is the Normalized Least Mean Square adaption constant and c is the constant term for normalization. α helps optimize the convergence rate for the algorithm and its value is between zero and two. The constant term for normalization c should always be less than one. Due to this alternate version of μ in the Normalized Least Mean Square algorithm, the filter coefficients are updated using the following equation:

$$w(n+1) = w(n) + \frac{\alpha}{c + \| x(n) \|^2} e(n)x(n)$$

3.5 Recursive Least Squares Algorithm

Like the LMS algorithm, the RLS algorithm uses some of the fundamental adaptive filter concepts. The RLS algorithm converges on the optimal solution by updating coefficients for each iteration of the algorithm until the optimal solution is reached. Similarly, in order to update the coefficients, the RLS algorithm performs three main steps, which include calculating y(n) from the adaptive filter, calculating e(n), and then finally updating the filter coefficients. Although the main overall process is similar for the LMS and RLS algorithms, the method used to update the coefficients are significantly different.[21,26]

First, the RLS algorithm can find the output of the filter using the following equation:

$$\bar{y}_{n-1}(n) = \bar{w}^T(n-1)u(n)$$

where $u(n)$ is the filter input vector of time delayed input values

$$u(n) = [x(n)x(n-1)x(n-2)\dots x(n-N+1)]^T$$

and $w(n)$ is the filter coefficients vector at time n

$$w(n) = [w_0(n)w_1(n)w_2(n)\dots w_{N-1}(n)]^T$$

Then, the following equation is used to calculate the error signal e(n):

$$\bar{e}_{n-1}(n) = d(n) - \bar{y}_{n-1}(n)$$

And finally, the filter coefficients are updated using the following equation:

$$w(n) = \bar{w}^T(n-1) + k(n)\bar{e}_{n-1}(n)$$

where $k(n) = \frac{v(n)}{\lambda + u^T(n)v(n)}$,

v$(n) = \overline{w_\lambda^{-1}}(n-1)x(n)$,

and λ is a small positive constant that is less than one (but usually close to one).

Due to needing previous values of the samples in addition to current values, more memory is required when using the RLS algorithm. However, the RLS algorithm has a much better convergence time compared to the convergence time of the LMS algorithm.

CHAPTER 4

ARTIFACT CANCELLATION SYSTEM MODELING

Below is an overview of the artifact cancellation system in Simulink. There are two inputs to the adaptive filter. The first input, named “Input”, is the primary input, which is the EEG signal. The secondary input, named “Desired”, is a reference input for the noise. The EEG signal (primary input) is corrupted with noise, which has a correlation with the reference noise (secondary input).

The adaptive filter has three outputs. The first output, named “Output”, gives the estimate of the noise, which becomes more accurate as the system converges. The second output, named “Error”, decreases and goes to zero as the system converges. The third output, named “Wts”, shows how the filter coefficients are updated over time to help reach the optimal solution. The first output, named “Output” is subtracted from the original EEG signal, in order to get a signal with the artifacts removed. The mathematical calculations using these inputs and outputs in the adaptive filter algorithms was explained in Chapter 3.

Three different artifact cancellation system models are shown in Simulink. Each different artifact cancellation system model utilizes a different adaptive filter algorithm. Figure 8 shows the system implementing the Standard LMS algorithm, Figure 9 shows the system implementing the Normalized LMS algorithm, and Figure 10 shows the system implementing the RLS algorithm.

The reference noise will change depending on the model for the stimulation or motion artifacts, which was explained in Chapter 2. Based on the type of artifacts that are present, a reference noise will be selected and used in the system. The noisy signal and reference noise will be the inputs into the system, and the clean signal will be one of the outputs. The results from utilization of these models are discussed in Chapter 5.

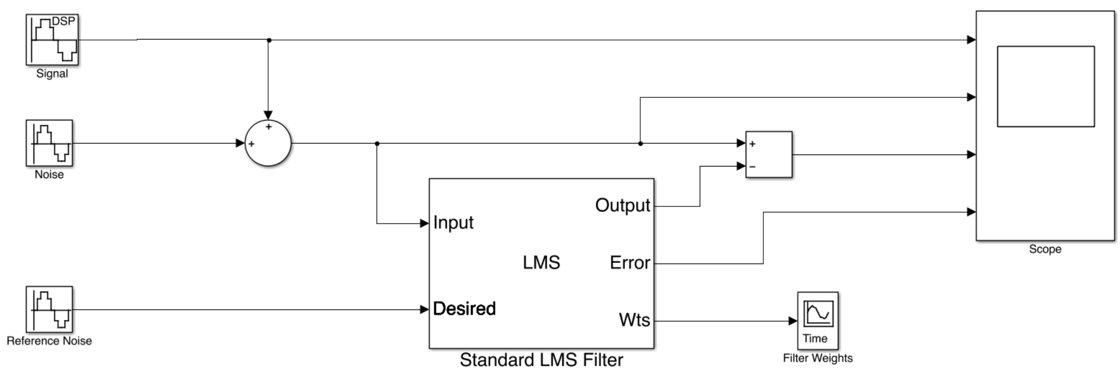

Figure 8: Standard LMS System In Simulink

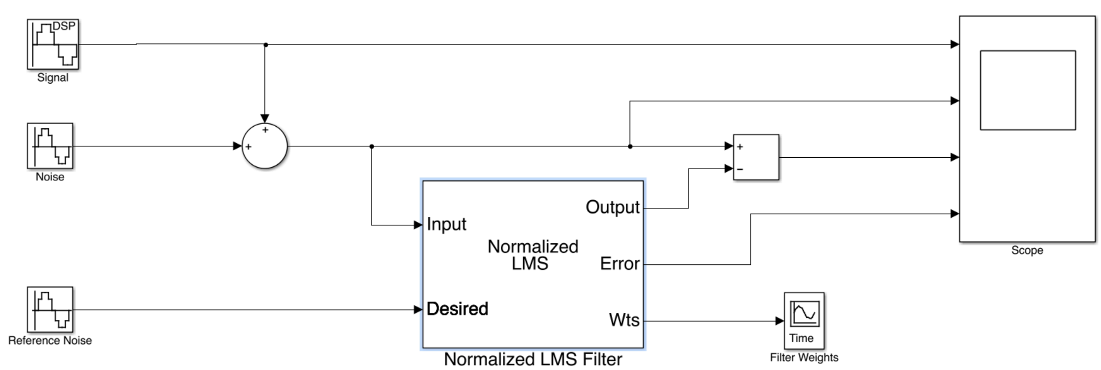

Figure 9: Normalized LMS System In Simulink

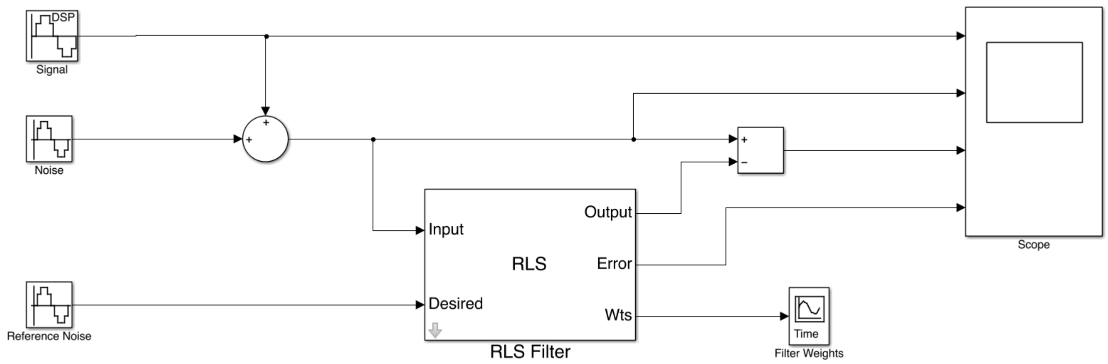

Figure 10: RLS System In Simulink

CHAPTER 5

RESULTS

Figure 11 shows the results of using the Standard LMS algorithm (Simulink model shown in Figure 8). The figure is divided into four graphs. The top graph is the original signal without any noise added. The second graph is the signal with noise added, causing a corrupted signal. The adaptive filter is supposed to remove that noise in order to get the original signal with no noise back. This signal with the noise removed is shown in the third graph, and the error is shown in the fourth graph. As mentioned in Chapter 3, the Standard LMS algorithm sometimes suffers from divergence issues, which occurred in this case and is shown in the third and fourth graphs of Figure 11. Due to the divergence issues, the original signal cannot be recovered and causes an error in the graph.

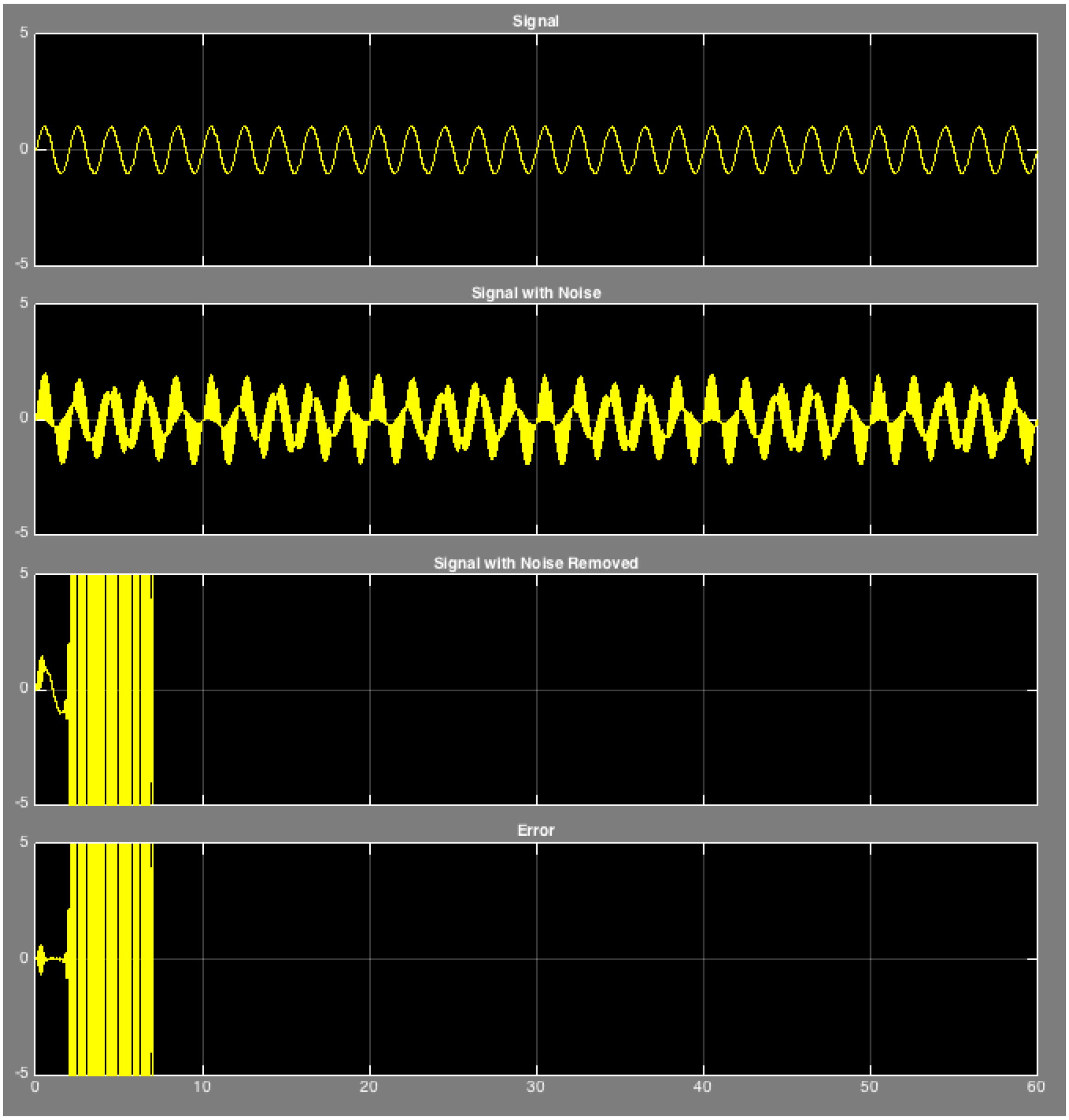

Figure 11: Results For Standard LMS System

The Normalized LMS algorithm is used to solve this problem, as shown in Figure 12. Again, the figure is divided into four graphs, with the first graph being the original signal and the second graph being the corrupted signal. The third graph should display the signal with the noise removed. It is shown that the normalized version successfully solves the problem since the original signal can be recovered. The Normalized LMS algorithm takes some time to converge, so initially there is still some noise present, which is shown in the third and fourth graph. The error decreases as the algorithm converges, and as the error goes to zero, the signal is filtered to become closer to the original signal.

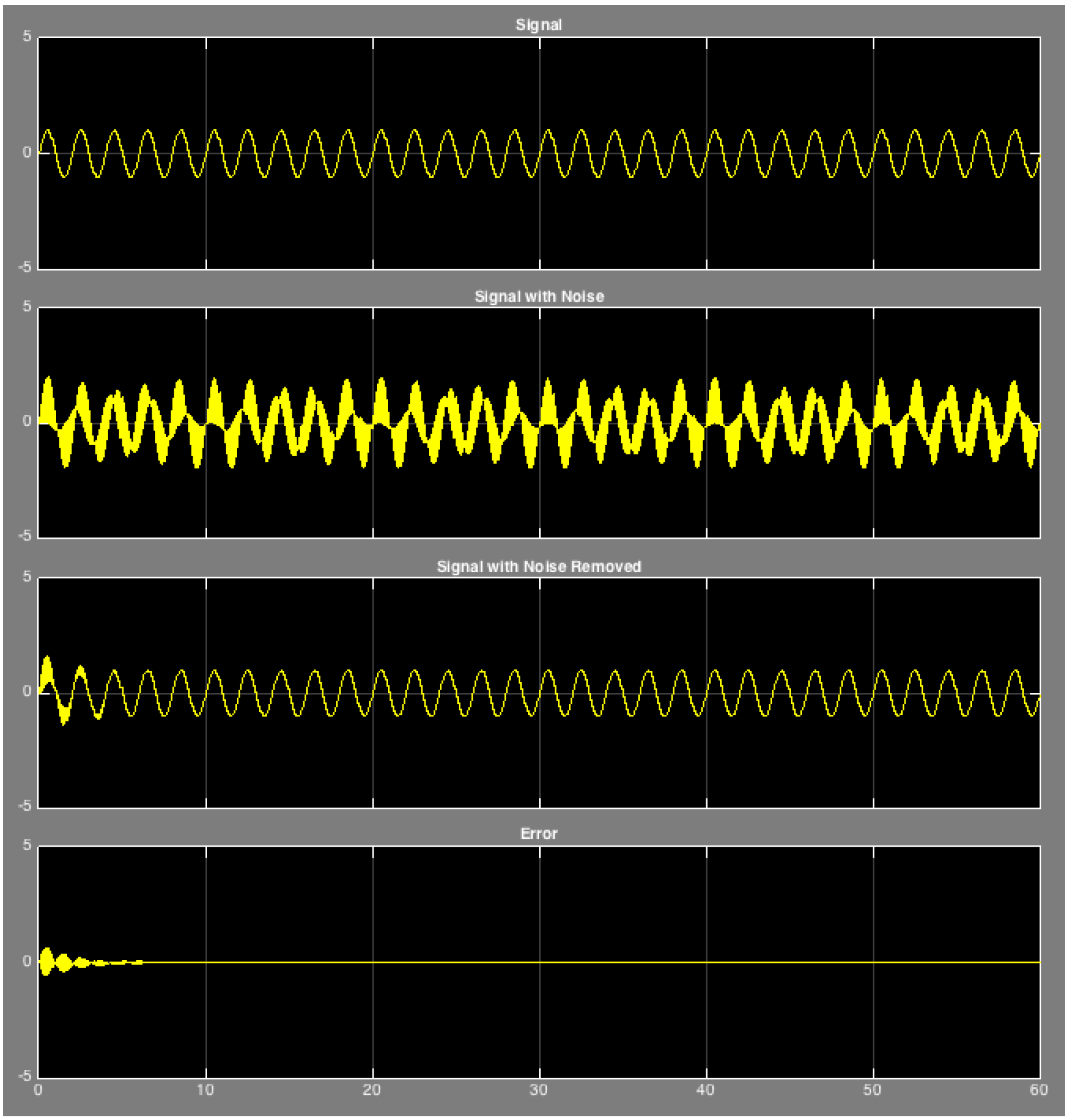

Figure 12: Results For Normalized LMS System

Figure 13 shows the results when using the RLS algorithm (Simulink model shown in Figure 10). Similarly, the top graph is the signal, the second graph is the corrupted signal, the third graph is the signal with the noise removed, and the fourth graph is the error. As explained above, the RLS algorithm converges much faster than the Normalized LMS algorithm. This is shown in the fourth graph, where the error goes to zero very quickly. In addition, in the third graph, the noise is present for only a very short period of time before the original signal is recovered. When using the Normalized LMS algorithm, the noise is present in the signal for a longer period of time. This improvement when using the RLS algorithm is possible because the RLS algorithm converges quicker than the Normalized LMS algorithm converges, although at the cost of higher complexity and required memory.

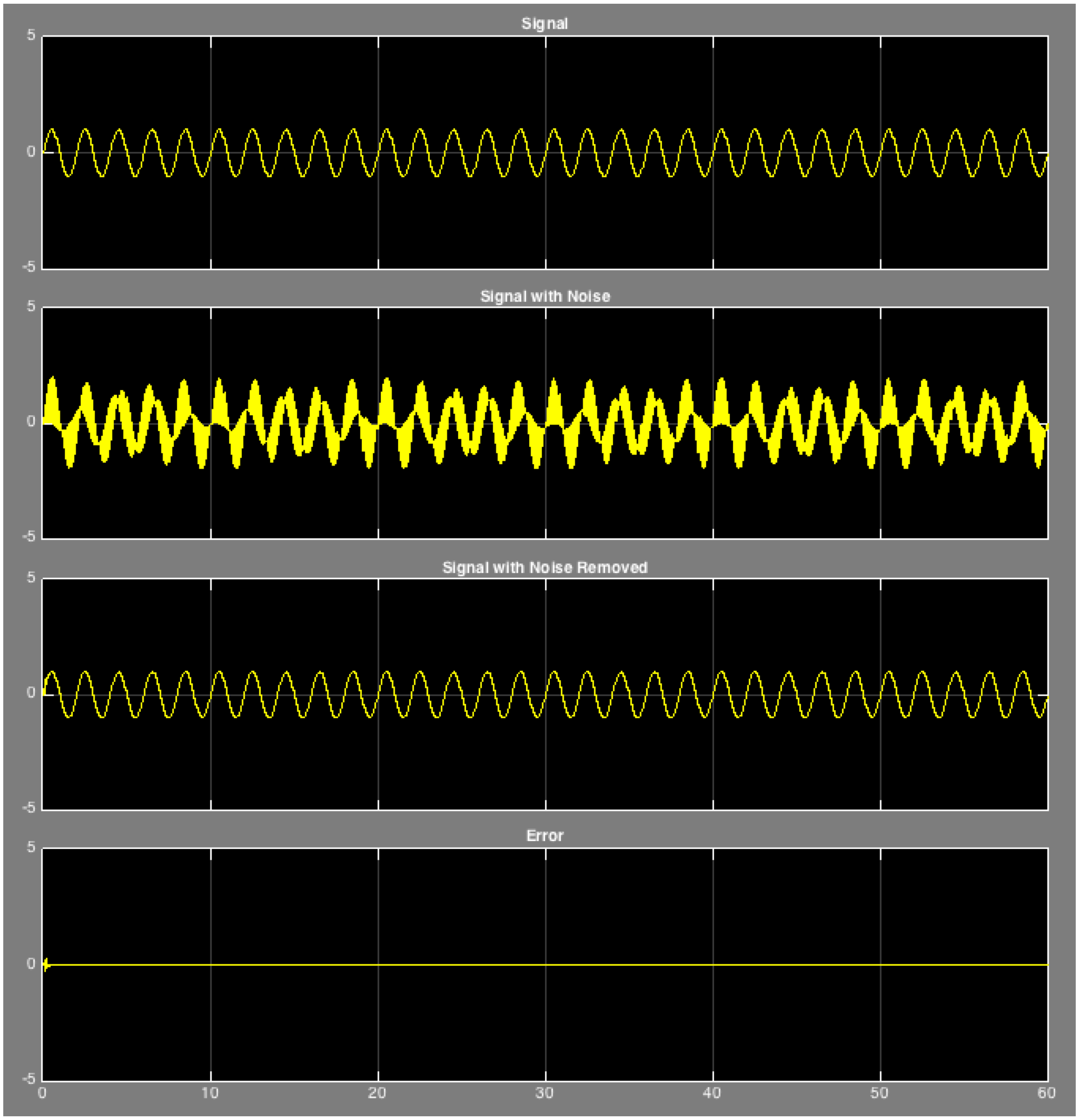

Figure 13: Results For RLS System

CHAPTER 6

CONCLUSION

Motion and stimulation artifacts can reduce the quality of EEG signals, which is a significant problem. The proposed method to solve this problem is using Matlab and Simulink in combination with external circuit components to remove the artifacts. For motion artifacts, an analog front end will retrieve the EEG signal and the impedance signal from the skin through an electrode. Then, using digital processing, the motion artifacts will be estimated from the measured impedance signal and the EEG signal that contains the motion artifacts. Once the motion artifacts are estimated, they can be removed by utilizing the adaptive filter models in Matlab and Simulink. Similarly, for stimulation artifacts, the signal is sampled in order to find a reference for the stimulation artifacts, and then the same adaptive filter concepts are utilized in order to remove the stimulation artifacts. There are multiple adaptive filter algorithms that can be used to remove the artifacts, including the LMS algorithm and the RLS algorithm. The Standard LMS algorithm can suffer from divergence issues, but the Normalized LMS algorithm fixes this problem. In addition, the RLS algorithm converges faster than the LMS algorithm but at the cost of higher complexity.

These different artifact cancellation systems can be modeled in Matlab Simulink. Using these methods, the motion and stimulation artifacts can be removed from the EEG signal in a quick and successful way, allowing for a more accurate reading of electrical activity of the brain.

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