Seizure Detection and Closed-Loop Control

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***Abstract*—This report explores closed-loop seizure mitigation. This requires a detector that can indicate seizure onset and a controller that can provide timely stimulation to stop the seizure. A machine-learning classifier is used to detect seizures and evaluate it on both real and simulated data. Control schemes that can stop a seizure in different simulation models are studied. Ultimately, these methods are far-removed from anything that would work robustly in practice, but this exploration offers insights into the challenges of successful seizure prevention.**

I. Introduction

Closed-loop control aims to use real-time data to detect epileptic seizures and deliver targeted electrical stimulation to the brain. This emerging field has the potential to improve the quality of life for people with epilepsy by reducing the frequency and severity of seizures. Advances in computation and machine learning has given rise to new techniques for better seizure mitigation. Mathematical frameworks have been developed to help predict and control seizure activity in highly personalized settings [1].

Numerous researchers work on modeling and experimentally verifying the dynamics of seizures. In this report, we rely on a model proposed by Suffczynski et al. [2], as well as a model proposed by Liou et al. [3] that more faithfully captures the spatial connection between neurons. Detection schemes involving feature-based thresholding and multiple machine learning models are demonstrated. Closed loop control is demonstrated using a Simulink model that incorporates a basic form of artefact mitigation. We further explore synchronized control based on the 2D rate model for the management of epilepsy.

II. Seizure Models

A. Thalamocortical Seizure Model

The thalamocortical circuit model [2] improves on the model proposed by Lopes da Silva et al. [4]. It incorporates low-threshold calcium currents [5] of the thalamic cells and both fast $GABA_A$ and slow $GABA_B$ receptor-mediated inhibitions.

The Thalamic loop consists of a population of thalamocortical (TC) cells and Reticular Thalamic (RE) cells. The Cortical loop consists of Pyramidal Cells (PY) and Inhibitory Cells (IN). The RE inhibits TC through GABAa and GABAb pathways. The TC receives excitatory input from the ascending pathway (Sensory). The RE receives inhibitory input from the surrounding RE population. PY cells receive excitatory input from surrounding PY populations. PY excites TC and RE, while TC excites PY and IN. Recording and stimulative interaction is carried out at the Pyramidal cells. Figure 4 represents the model and the closed-loop control introduced as a part of this work.

Receptors: $GABA_A$ receptors are responsible for fast synaptic inhibition. $GABA_B$ receptors are responsible for slow synaptic inhibition. AMPA receptors facilitate depolarization of the membrane and increase the likelihood of the neuron firing.

B. Underlying Spatio-temporal Patterns

In order to view a complementary simulation with respect to the one above, we explore a seizure model presented by Liou et al. [3] which, among other things, simulates the mechanisms that are hypothesized to cause seizures and produces spatio-temporal patterns that correspond to the canonical stages of a seizure. They identify patterns corresponding to the tonic-clonic transition, slow advance of seizure territory expansion, widespread EEG synchronization, and slowing of the ictal rhythm. In this paper, the primary model used for simulation was a '2D-Rate-Model, (shown in Figure 5) which models the neocortex as a 2-dimensional neuron sheet, with neurons that are recurrently connected by direct excitatory projections, and also inhibit each other indirectly through di-synaptic pathways via inter-neurons [3]. This simulation generates 2D visualizations of the voltage and ion concentrations across a 2D brain.

III. Methods

The challenge of robust seizure detection and control is highly complex because of high individual variability and lack of high-fidelity data. With that being said, we try to gain an intuition for different components that are needed for a seizure controller by approaching the following sub-problems:

- **Seizure Detection:** We explore a simple feature detector and a machine-learning approach in classifying seizures.
- **Closed-Loop Control:** Stimulating impulses of different modalities are used for closed-loop control.

A. Seizure Detection

1) Simple feature Detection

A Simulink Model is designed to detect seizures based on Line length. This feature was chosen due to its simplicity, reliability, and ability to detect changes in signal morphology, as we learned from the lab on seizure detection. The data was sampled at 500Hz and sectioned into overlapping bins of 200ms. The line length threshold was decided based on an analysis of 10 randomly generated 100-second waveforms.

2) Machine Learning based Detection

The seizure detection was improved with a machine learning model trained on real EEG data collected from the UCI Machine Learning Repository [6]. The dataset consisted of 500 individuals, each with 4097 data points representing a recording of brain activity for 23.6 seconds. These data points were divided and shuffled into 23 chunks, each containing 178 samples of 1 second. The last column in each chunk represented the label, which was categorized into five classes representing different states of brain activity. To detect seizures, the non-seizure classes were combined to make it a binary classification problem, with 9200 records belonging to the non-seizure class and the rest 2300 records belonging to the seizure class. Some of these signals are visualized in Figure 6.

The data was split into training and testing with 80-20 ratio. Prior to analysis, the data was standardized to ensure consistent scale and variance across features. Logistic Regression, Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Gaussian Naive Bayes algorithms were used to compare the performance. The model with the best performance was chosen to detect the seizures simulated by the Simulink model. Simulink generated multiple 100-second signals with different seeds, each sampled at 1KHz. However, the Machine Learning model used for seizure prediction was trained on data sampled at 178Hz. The signals were resampled at 178Hz using linear one-dimensional interpolation and divided into 100 chunks of 1 second each. The best ML model was then used to classify each chunk as either seizure or non-seizure. This information is utilized to develop control signals for closed-loop systems.

B. Closed loop Control

Seizure Control was implemented using the block diagram shown in Figure 1. Figure 9 shows the entire Simulink model. After feature extraction and thresholding, short 100ms pulses of stimulation are applied to the network at the onset of seizures. The recording and stimulation are applied to the pyramidal cells to better simulate the constraints of real closed-loop control. Artefact mitigation is achieved through logic designed to disable recordings during

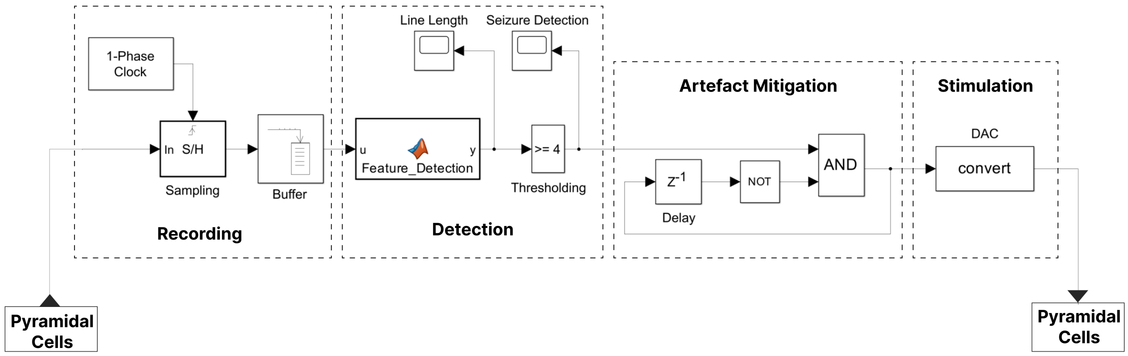

Fig. 1: Block Diagram of Seizure Control implemented in Simulink

ongoing stimulations. The stimulus is applied using different current pulses.

1) Control of 2D rate model

To determine the generalizability of the simple voltage-pulse control method, we also applied a similar synchronized pulse to the 2D-Rate-Model of Liou et al. [3], which simulates the evolution of seizures over time and space. The initialization parameters of the 2D-Rate-Model are chosen so as to spontaneously generate a seizure. Different Lengths, strengths, and timing of the neural impulse are studied. It is possible to end the patterns by applying a synchronized voltage pulse with duration and amplitude on the order of $30ms$, 200 μA. Sometimes the seizure would end spontaneously, but about 3 out of 10 times, the synchronized pulse was the only way to end the seizure.

IV. Results

A. Seizure Detection

The classification accuracy obtained for each of the four machine learning models are tabulated below in Table I. Among these different machine learning models evaluated for seizure classification on the simulated data, SVM performed the best and was therefore selected for the task.

Accuracy		
Algorithm	Training Accuracy	Testing Accuracy
LgR	82.27%	82.22%
SVM	98.25%	**96.96%**
kNN	93.85%	92.78%
gNB	95.74%	95.83%

TABLE I: Classification accuracy of the machine learning models

B. Seizure Control

Can mitigation be achieved for different pulse width and stimulating currents? Seizure Control was demonstrated using different stimulating pulses. Figure 2 represents stimulation with varying amplitudes of stimulating currents. Mitigating can be achieved more quickly with higher stimulating currents. Mitigation was achieved after applying 5mA pulses for 2.5 seconds (Fig.2 B,C), whereas 10mA pulses for only 0.5 seconds were needed to achieve the same result (Fig.2 D,E). Another key aspect of the closed-loop stimulation algorithm is the artefact mitigation. Fig 10 A shows a neural waveform with seizure. If stimulation is performed without artefact mitigation we get Fig 10 C. This is because the stimulations are perceived as artefacts. After artefact mitigation we obtain the waveform seen in Fig 10 E.

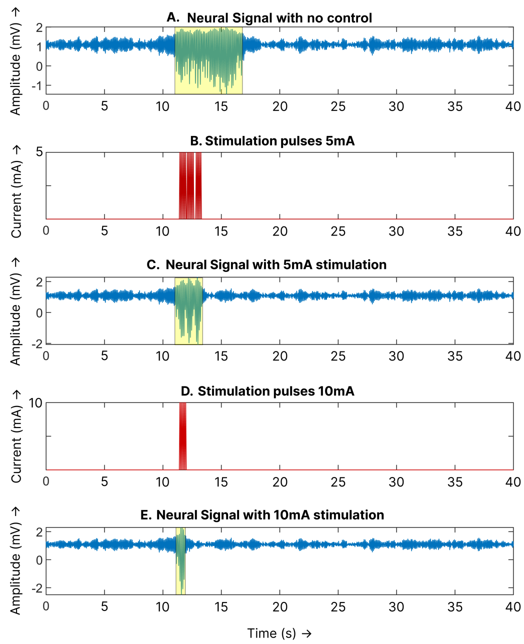

Fig. 2: A. Regular neural activity. B. 5mA stimulation based on closed-loop control, C. Neural activity with 5mA stimulation, D. 10mA stimulation based on closed loop control, E. Neural activity with 10mA stimulation

C. *Controlling the 2D-Rate-Model*

Can understanding the underlying spatiotemporal pattern help decrease stimulating power? A synchronized control was applied to the 2D-Rate-Model to mitigate the seizure pattern. The evolution of the seizure is shown in Figure 3, as well as the clear diminishing of the seizure when a synchronizing input was applied. The 2D rate model required a control input of the order of $30ms$, 200 μA to control the seizure. The Thalamocortical Model however required at least 5mA of stimulation for 200ms. Although these models cannot be directly compared, it is clear that understanding the underlying spatio-temporal patterns can significantly decrease the stimulating current and allow for low-power devices.

V. Discussion

This work takes a broad approach to seizure detection and control, presenting a seizure classifier

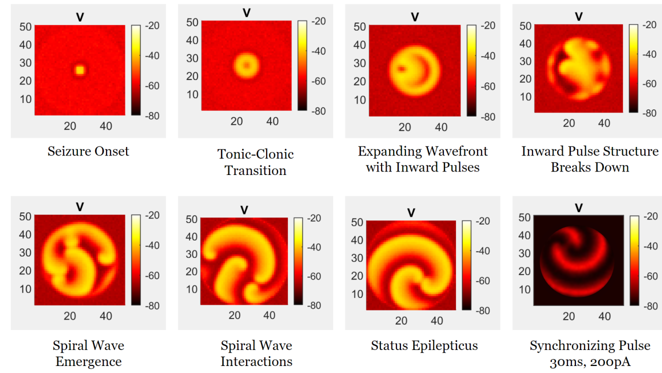

Fig. 3: Seizure evolution generated by a 2D-Rate-Model. Three out of ten simulations continue indefinitely in a spiral pattern, which is analogous to ”seizure epilepticus” (prolonged seizure) symptoms. In the end, a synchronizing input is applied that ends the seizure.

as well as control schemes that works in a simulated environment. Consequently, there exists scope for improvement within each specific sub-task. There are many problems to solve before these techniques provide a fully robust cure for epileptic seizures. That being said, they are critical in the pursuit of understanding the origins of seizures and more broadly the delicate balance that normally allows our brain to accomplish great feats on a daily basis.

The machine learning models can be implemented on an FPGA and studied to understand performance and power constraints. Another novel approach is to pipeline classification into two stages. The EEG signals are decomposed using discrete wavelet transform into features in the first stage followed by the use of a deep neural network classifier. The work by Sayeed et al. [7] demonstrates this while analyzing hardware constraints.

The clear flaw in the control algorithms is that these techniques were able to stimulate all neurons simultaneously and precisely, which is far removed from any control scheme that could be implemented using actual electrodes. An interesting extension of the 2D rate model would be to create an electrode in the simulated environment and see how *localized* inputs could still disrupt and end the patterns of the seizure [8].

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APPENDIX

A. *Figures*

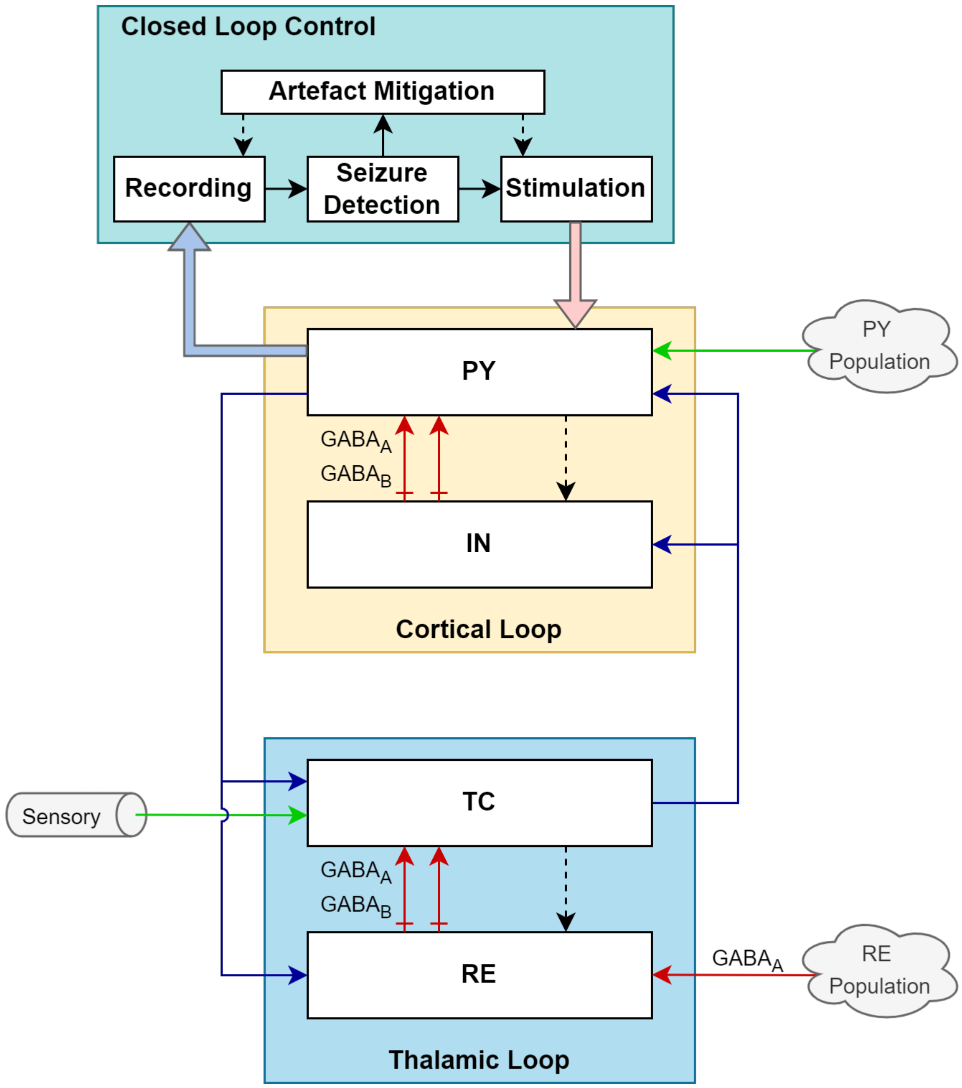

Fig. 4: Block Diagram of Siezure Model. Green lines indicate excitatory AMPA pathways. Red lines indicate inhibitory pathways

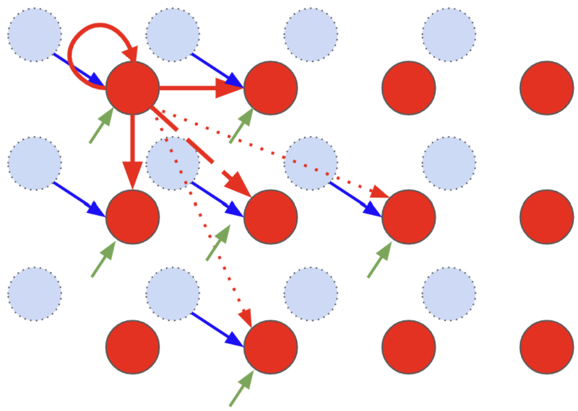

Fig. 5: 2D-Rate-Model schematic from Liou et.al. [3] Red circles: model neurons. Blue circles: inhibitory neurons. Red Arrows: excitatory recurrents. Blue arrows: di-synaptic recurrent inhibition. Green Arrows: Control Input (strength of connections is distance-dependent and indicated by arrow dashes). All neurons are connected in the same pattern, even if not shown.

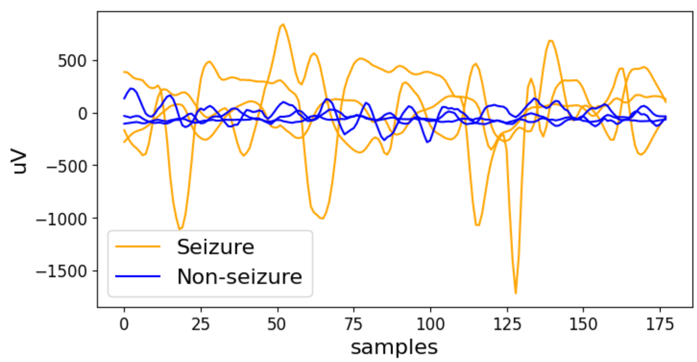

Fig. 6: Some of the seizure and non-seizure EEG signals from UCI ML Dataset

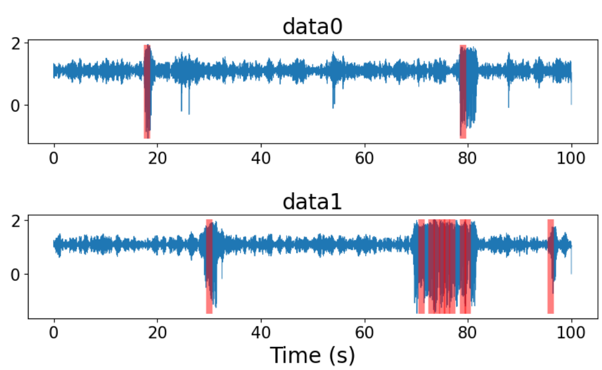

Fig. 7: Detection of seizure using SVM trained on UCI dataset on two different signals generated by Simulink model. The red vertical lines correspond to the seizure detections, and blue lines represent the actual signal

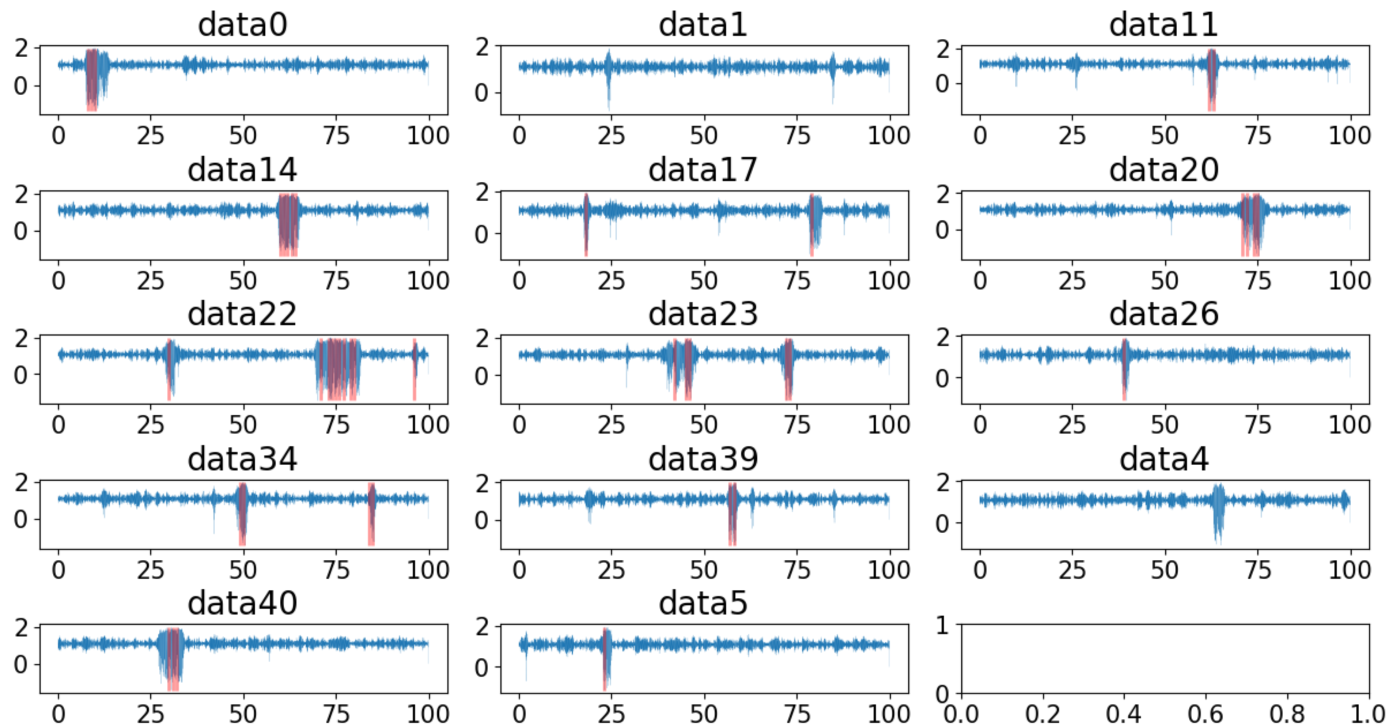

Fig. 8: Detections of seizure using SVM trained on UCI dataset on 14 different signals generated by Simulink model. The red vertical lines correspond to the seizure detections, and blue lines represent the actual signal

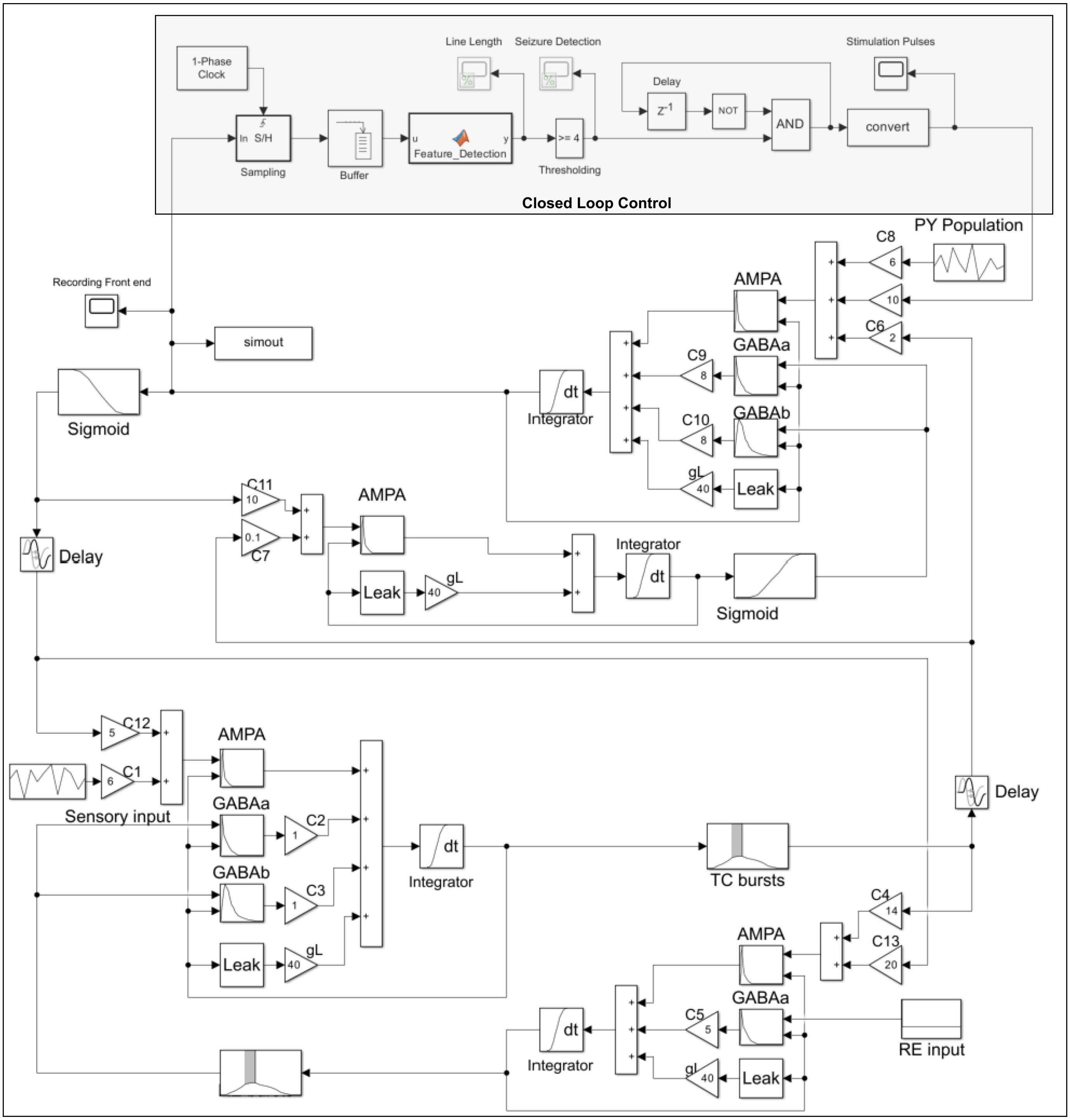

Fig. 9: Complete Simulink Model and Closed Loop Control

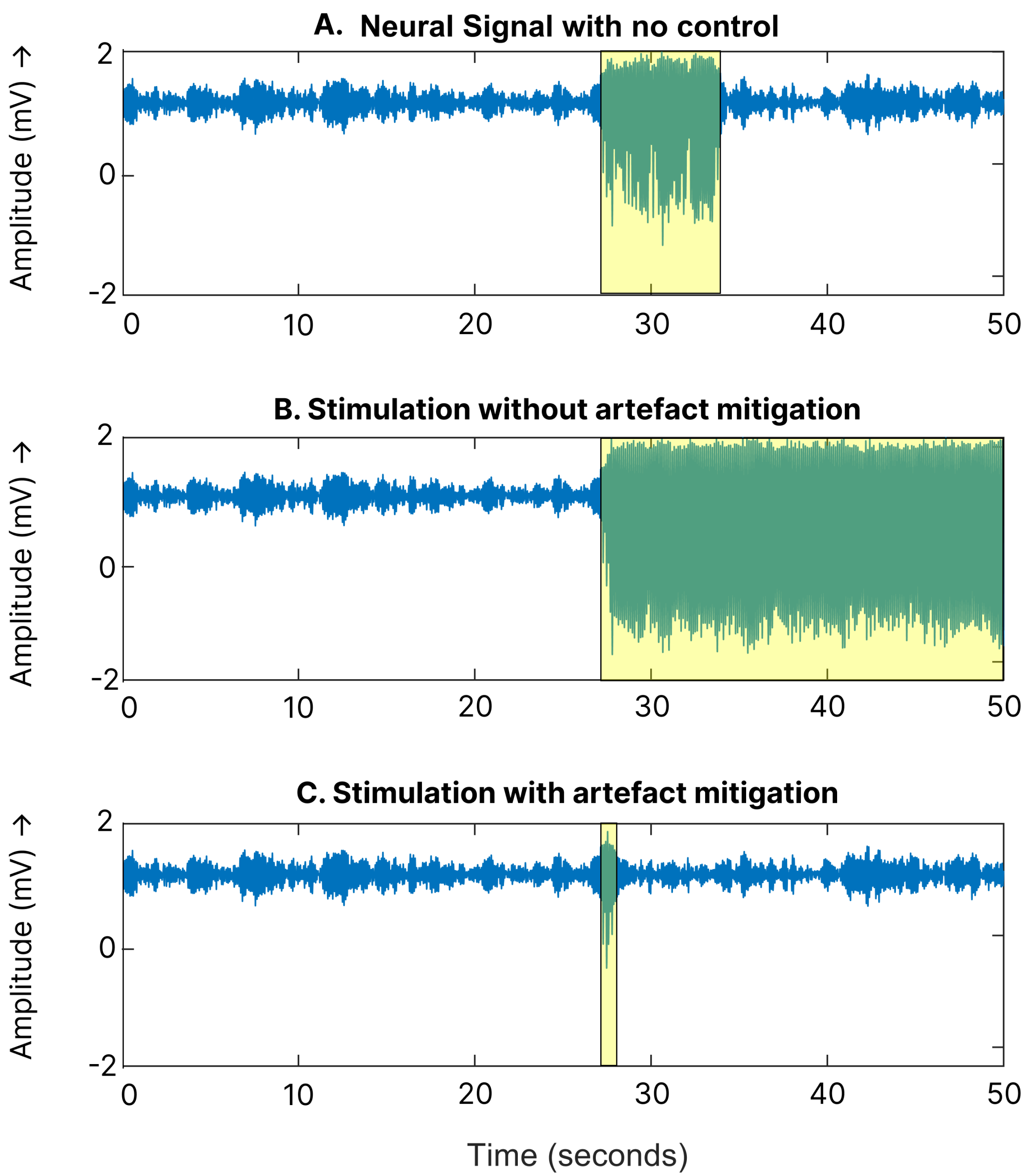

Fig. 10: Artefact Mitigation demonstrated on simulated data