Exercise #1: Intra-cellular recordings in a current-clamped cell

Anton Pasternak

Introduction

Neural spike detection is a critical step in analysing electrophysiological data, allowing us to quantify neuronal activity. The goal of this analysis is to detect action potentials in recorded voltage signals, determine their timing, and compute the firing rate over distinct time segments. This document outlines the methodology used in this process, accompanied by plots of the results.

Methodology

There are two datasets, S1 and S2, recorded at a sampling rate of 10 kHz. These data are of neuronal intra-cellular voltage recordings, in which every 0.3 seconds a DC current is injected into the cell for 0.2 seconds. One of the first challenges in spike detection is determining a suitable voltage threshold for identifying action potentials. A challenge that was solved for us, as a threshold of -30 mV was predefined in the supplied code.

Preprocessing and Threshold Crossing Detection

The raw signals undergo threshold-based spike detection, where each data point is compared against the predefined threshold. A binary representation of threshold crossings is created to track when the signal surpasses the threshold. The algorithm also identifies transition points where the signal moves from below to above the threshold (low-to-high transitions) and vice versa (high-to-low transitions).

Local Maxima Identification and Spike Timing

Once the threshold crossings are determined, the next step involves finding the local maxima of the signal between each pair of low-to-high and high-to-low transitions.

Segmented Firing Rate Computation

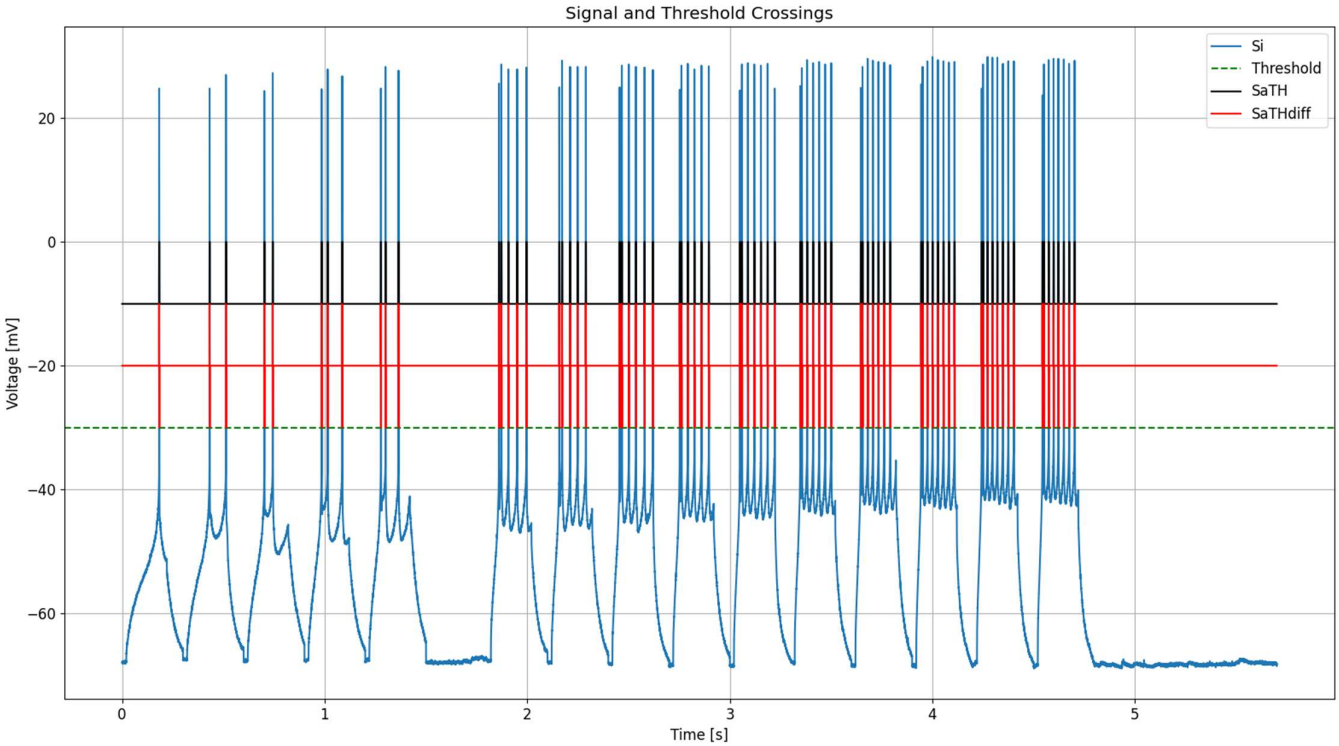
To better understand the neuronal activity, the firing rate is computed for distinct segments of the signal. Each segment corresponds to a defined stimulus cycle duration of 0.3 seconds. Within each segment, the number of detected spikes is counted and converted to a firing rate by dividing by the DC segment duration (0.2 sec).

To provide a more robust estimate of neuronal firing variability, two different measures are used:

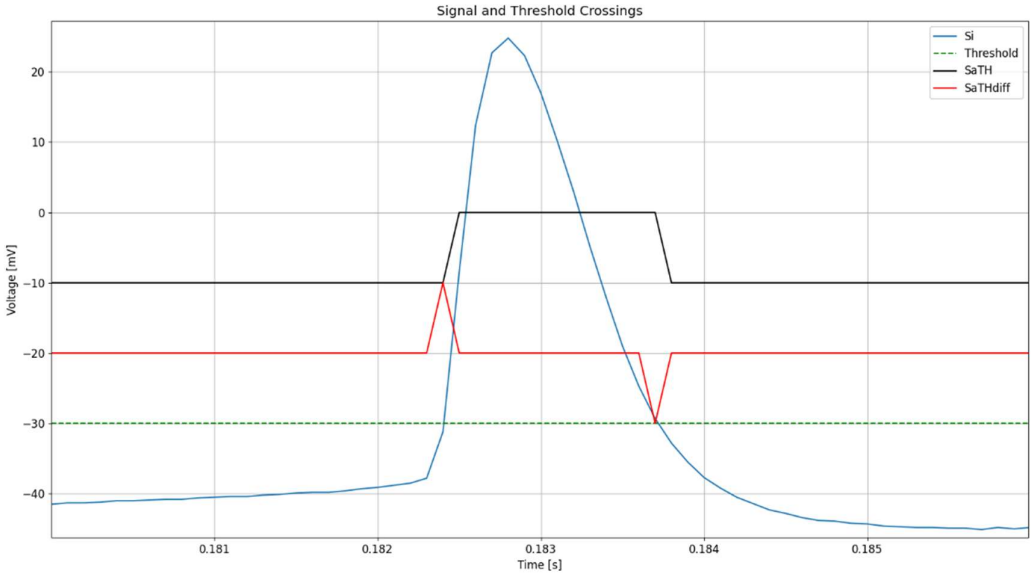
- **Mean Firing Rate**: A simple average of spike occurrences, which can be more sensitive to extreme values.
- **Median ± Standard Deviation**: This method accounts for variability in inter spike intervals while reducing the influence of outliers.

Results

Data Set S1: Initial Processing

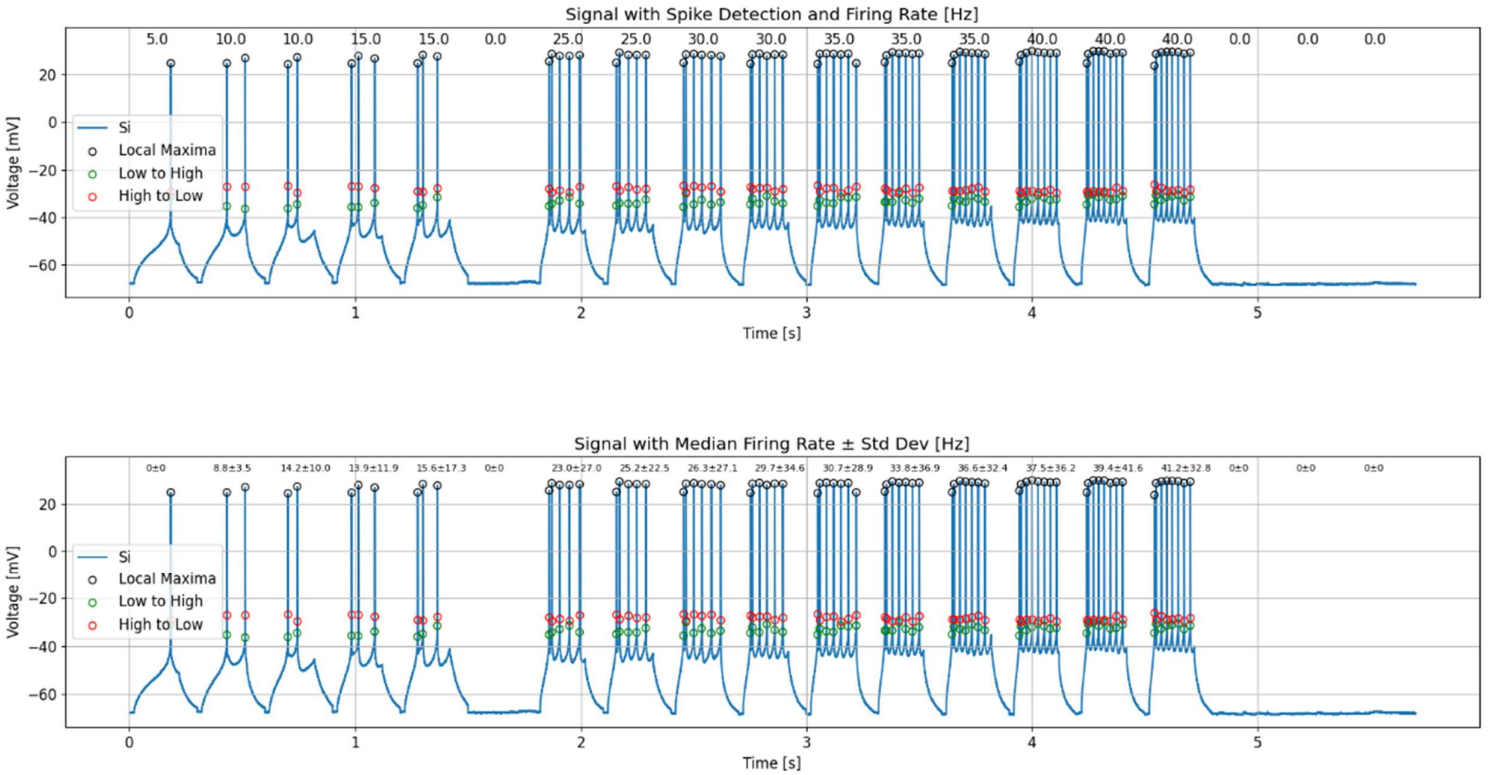


The is the first plot which visualizes:
Si- the signal of dataset S1.
Threshold- of -30mv.
SaTH- the detected threshold crossings (for convenience plotted as 10*SaTH-10).
SaTHdiff- the numpy diff function done on SaTH, that shows the direction of the crossing (for convenience plotted as 20*SaTHdiff-20).

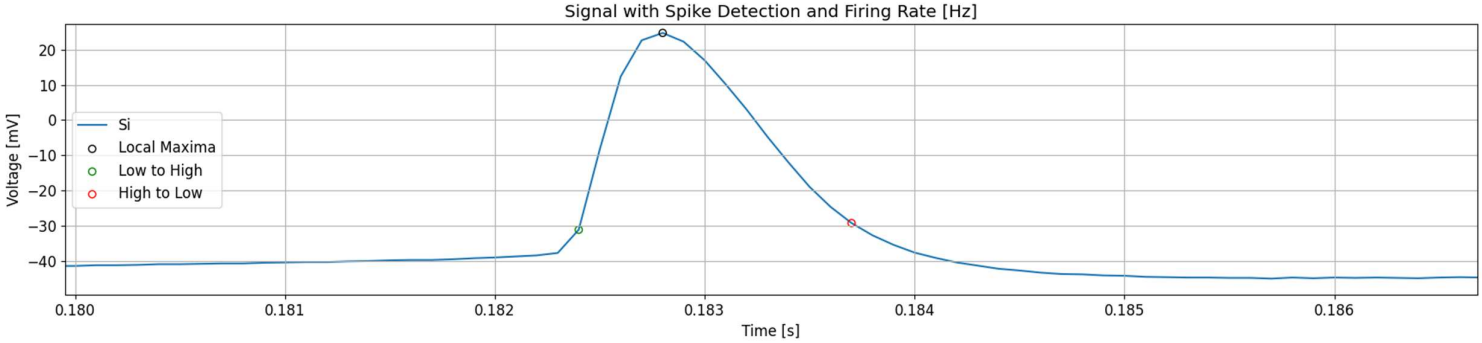


This second figure is a zoom into the first spike region of the first plot.

Data Set S1: Firing Rate Analysis

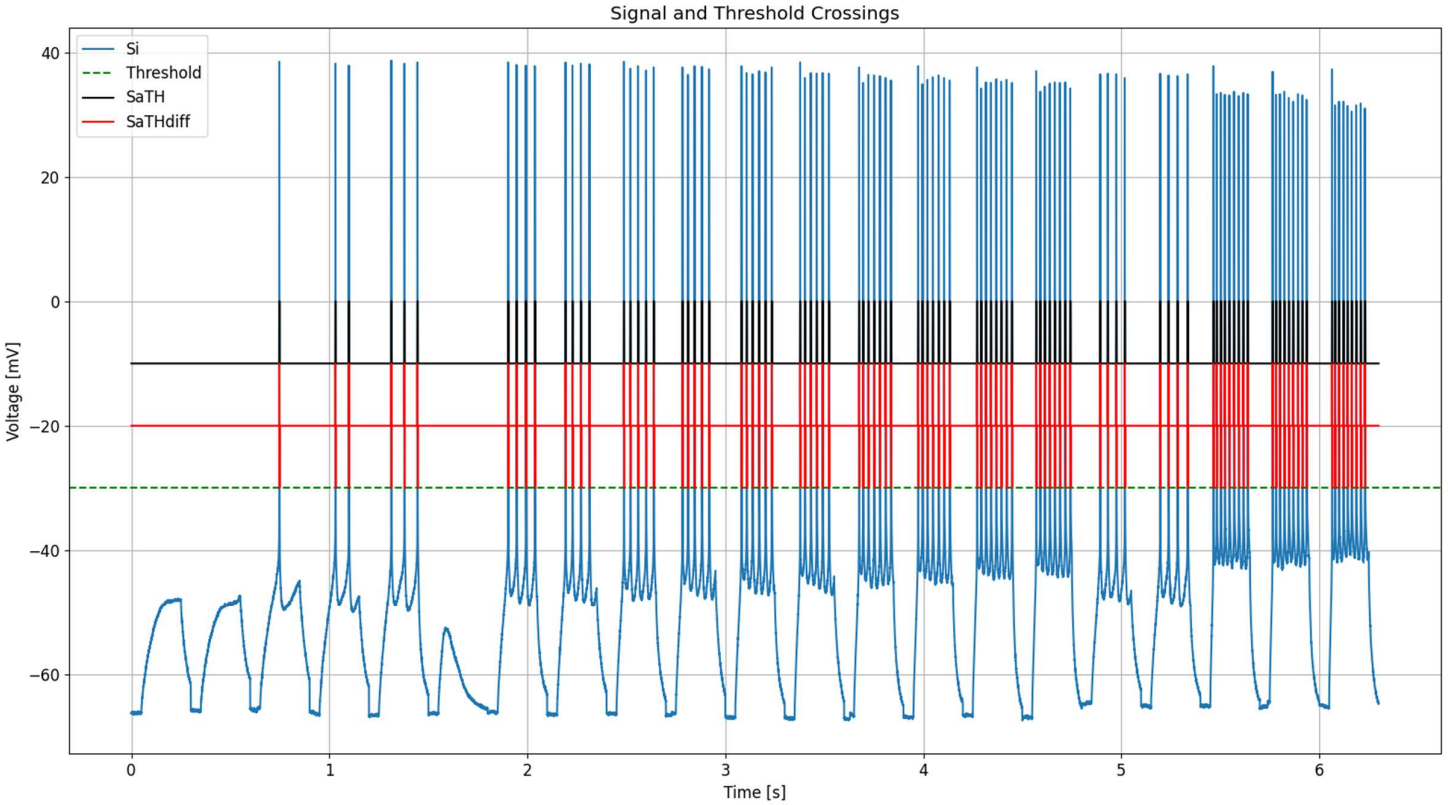


The second plot consists of two subplots. The upper subplot shows the raw signal with detected spikes, while the lower subplot presents the computed firing rates over time. The blue trace shows the original signal, while the black dots indicate detected local maxima. The red dots mark transitions from high to low and the green dots low to high. Each segment is annotated with its median firing rate ± standard deviation. The median is preferred over the mean because it minimizes the effect of extreme outliers, providing a more stable estimate of neuronal activity.



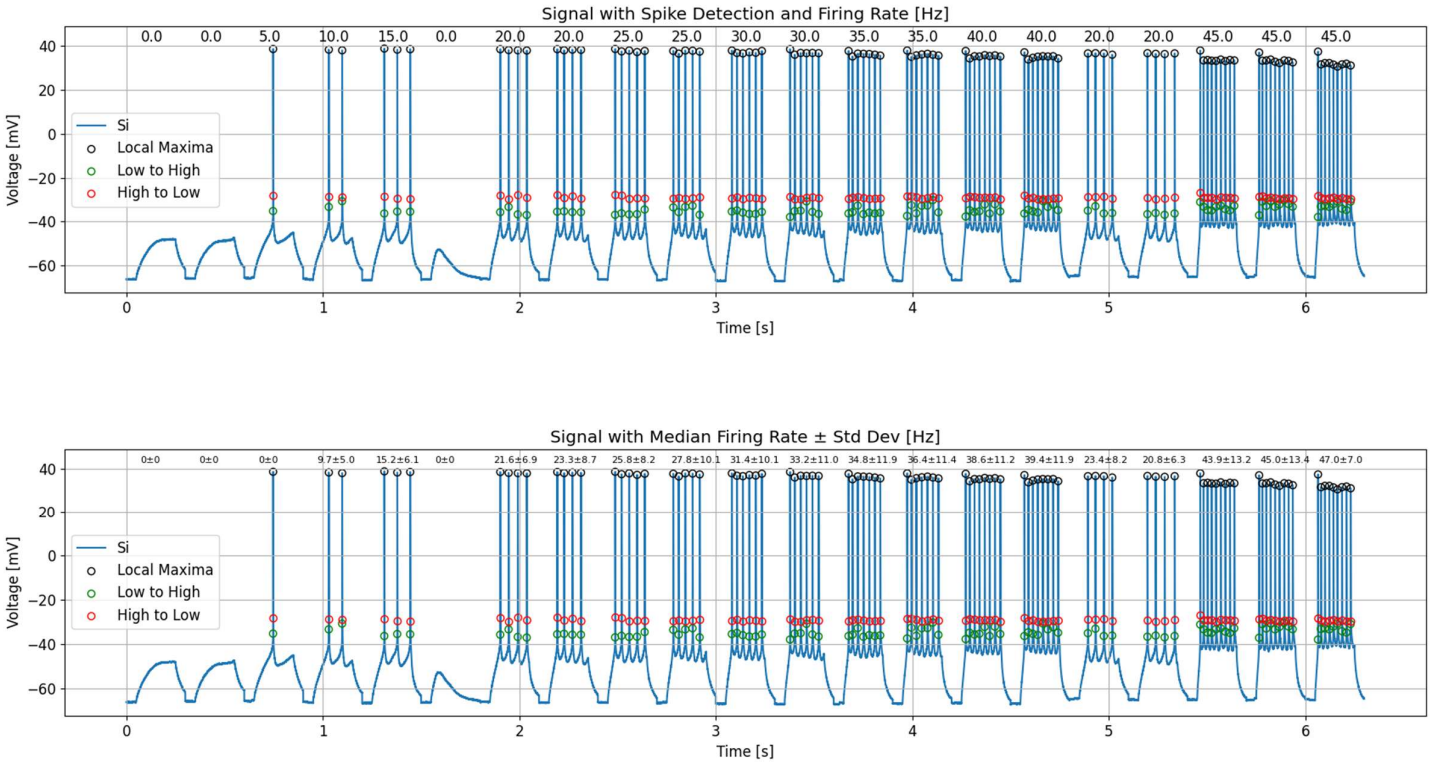
This figure also shows a zoom into the first spike

Data Set S2: Initial Processing



The first plot for dataset S2 follows the same structure as S1, displaying the signal, threshold, and detected spikes. This visualization allows us to confirm that the spike detection algorithm successfully identifies action potentials across different datasets.

Data Set S2: Firing Rate Analysis



The second plot for S2 shows the variation in firing rates across different stimulus segments. The difference between median ± standard deviation and simple averaging is highlighted here. While the mean provides a general idea of the firing rate, the median captures the central tendency more reliably, particularly when the firing rate fluctuates significantly.

Conclusion

This analysis demonstrates a robust method for detecting spikes and computing firing rates in electrophysiological recordings. By leveraging threshold detection, local maxima identification, and segment-based analysis, we can obtain reliable metrics for neuronal activity. Using the median ± standard deviation approach ensures that our results are not overly influenced by extreme values, making it a preferable choice for analysing neural firing rates.

Bonus

Both data sets show neuronal activity which has some “outliers” in the sense where some measured data isn’t as the rest of it; for instance, the sixth and the three last segments of S1 and the first, second and sixth segments of S2.
As for the outliers of S1, they are probably due to no current injection as it seems that the voltage stays pretty much constant around the resting potential of the cell.
As for the outliers of S2, they are probably due to not enough current injection as it seems that the cell voltage is rising but is not able to cross the threshold.