lab_notebook_saved_25_03_18

March 18, 2025

1 Data to explore

[ ]:
```
# Initialize the data structure as a list of tuples
data_to_explore = []

# Example of adding ABF files and sweep numbers as tuples
data_to_explore.append(("file1.abf", 1))
data_to_explore.append(("file1.abf", 3))
data_to_explore.append(("file2.abf", 0))
data_to_explore.append(("file2.abf", 2))

# Accessing the data
for abf_file, sweep_number in data_to_explore:
    print(f"ABF File: {abf_file}, Sweep Number: {sweep_number}")
```

[ ]:
```

```

---

2 abf files and pyabf library

2.1 ABF File Overview

An ABF (Axon Binary Format) file is a proprietary file format developed by Axon Instruments (now part of Molecular Devices) to store electrophysiological data from experiments. ABF files are commonly used to save data from experiments like patch-clamp recordings, where researchers measure electrical signals from biological systems (such as neurons or muscle cells). These files can store a variety of information, including:

- Data Traces: Time series data for one or more channels, representing signals such as voltage or current.
- Metadata: Information about the experiment, including settings for the recording, such as sampling rate, experiment type, and device configuration.
- Multiple Sweeps: An ABF file can contain multiple sweeps (individual trials or experimental runs), which may differ in parameters or conditions.

The ABF format is binary, making it efficient for large datasets, but it is not easily readable without specialized software or libraries.

2.2 pyabf Library

The `pyabf` library is a Python package designed to facilitate working with ABF files. It provides an easy-to-use interface to read and manipulate data stored in ABF files. The library makes it simpler for researchers to extract relevant information from ABF files, without having to manually parse the binary data.

Key Features of pyabf:

1. Load ABF Files: Load an ABF file into memory and provide access to its data.
2. Access Data Traces: Extract time-series data, such as voltage and current traces (from ADC channels).
3. Multiple Sweep Support: Handle multiple sweeps (individual experimental runs) within a single ABF file.
4. Extract Metadata: Retrieve metadata like channel names, experiment parameters, and other settings.
5. Sweep Navigation: Select and navigate through multiple sweeps (trials) and analyze their data individually.

Common Functions in pyabf:

- `ABF(file_path)`: Initializes an ABF object from a given file path, loading the data into memory.
- `setSweep(sweep_index)`: Selects a specific sweep (experimental run) by its index.
- `sweepY`: Extracts the voltage (or other signal) data for the current sweep.
- `sweepX`: Extracts the time vector for the current sweep.
- `sweepC`: Extracts the command input (if available) for the current sweep.
- `adcNames`: List of ADC channel names.
- `dacNames`: List of DAC channel names.

2.3 On the net

The pyABF library was created by Scott Harden. Scott Harden has made pyABF available as an open-source library, aiming to simplify the process of working with ABF files in Python, making it easier for researchers to analyze and visualize their data. You can find more about pyABF and its documentation on his website: pyABF - A simple Python interface for Axon Binary Format ABF files.

- pyABF - A simple Python interface for Axon Binary Format ABF files, with git repository
- a tutorial by [Scott W Harden]
- in Python Package Index pypi

2.4 Basics

Where we import the `pyabf` package and load a record file:

[1]:
```
import pyabf                                # load the pyABF library
file_path = "bursting/cell89basal.abf"  # we select the abf record file
abf = pyabf.ABF(file_path)              # we load it
print(abf)                              # record characteristics
```

```
ABF (v2.6) with 1 channel (pA), sampled at 10.0 kHz, containing 30 sweeps,
having no tags, with a total length of 11.11 minutes, recorded without a
protocol file.
```

Here `abf = pyabf.ABF(file_path)` creates an `abf` object that have: - **attributes**: data stored in the object, and - **methods**: functions that belong to an object and can be called to perform actions

We can print more attributes:

[2]:
```
print(f"{'File Path:':>20} {abf.abfFilePath}")
print(f"{'File Version:':>20} {abf.abfVersionString}")
print(f"{'Sampling Rate:':>20} {abf.dataRate} Hz")
print(f"{'Total Sweeps:':>20} {abf.sweepCount}")
print(f"{'ADC Channels:':>20} {abf.adcNames}")
print(f"{'DAC Channels:':>20} {abf.dacNames}")
print(f"{'Channel Units:':>20} {abf.sweepUnitsY}")
print(f"{'Experiment Date:':>20} {abf.abfDateTime}")
```

```
          File Path:
/Users/campillo/Documents/1-now/2025_abf_dpp/abf_data/bursting/cell89basal.abf
       File Version: 2.6.0.0
      Sampling Rate: 10000 Hz
       Total Sweeps: 30
       ADC Channels: ['Waveform']
       DAC Channels: ['AO #0']
      Channel Units: pA
    Experiment Date: 2024-11-08 00:00:50.086000
```

You can list all the attributes of an `abf` object with `print(abf.__dict__)`.

[3]:
```
methods = [method for method in dir(abf) if callable(getattr(abf, method)) and
 ↪not method.startswith("__")]
print("\n".join(methods))
```

```
_dtype
_getAdcNameAndUnits
_getDacNameAndUnits
_ide_helper
_loadAndScaleData
_makeAdditionalVariables
_readHeadersV1
_readHeadersV2
getAllXs
getAllYs
headerLaunch
launchInClampFit
saveABF1
setSweep
sweepD
```

You have private methods (Prefixed with _), and:

- `getAllXs()`: Returns all time points (X-values) for every sweep, useful for plotting.
- `getAllYs()`: Returns all recorded signal values (Y-values) for every sweep.
- `headerLaunch()`: Likely a utility function for debugging or inspecting header information.
- `launchInClampFit()`: Opens the ABF file in ClampFit, a software from Molecular Devices used for electrophysiology data analysis.
- `saveABF1()`: Converts and saves the ABF file in version 1 format, which is older but sometimes required for compatibility.
- `setSweep(sweepIndex)`: Sets the current sweep (i.e., trial or recording segment) to a given index for further processing.
- `sweepD`: Likely an attribute or method that provides the time duration of a sweep.

Of course the main parts of the sweep are the **recorded signal** and the **command inpput**:

[4]:
```
# Print voltage trace (recorded signal)
print(f"{'Voltage Trace (mV):':>25} {abf.sweepY}")

# Print command input (if available)
print(f"{'Command Input (mV):':>25} {abf.sweepC}")
```

```
      Voltage Trace (mV): [-61.2   -60.856 -61.2   … -56.228 -56.196 -56.353]
      Command Input (mV): [0. 0. 0. … 0. 0. 0.]
```

2.5 Basic abf file exploration

2.5.1 abf attributes and methods

The `abf` object contains various attributes and methods that allow you to access metadata and data from the .abf file. Here are some useful attributes and how to call them:

[5]:
```
print("List of sweep indexes:", ", ".join(map(str, abf.sweepList)))
```

```
List of sweep indexes: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,
17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29
```

[6]:
```
# Choose a specific sweep (e.g., first sweep -> index 0)
sweep_index = 0
abf.setSweep(sweep_index)

# Print voltage trace (recorded signal)
print(f"{'Voltage Trace (mV):':>25} {abf.sweepY}")

# Print command input (if available)
print(f"{'Command Input (mV):':>25} {abf.sweepC}")

# Check all available ADC channels (recorded signals)
print(f"{'Recorded Channels:':>25} {abf.adcNames}")

# Check DAC channels (command input signals)
```

```
print(f"{'Command Channels:':>25} {abf.dacNames}")
```

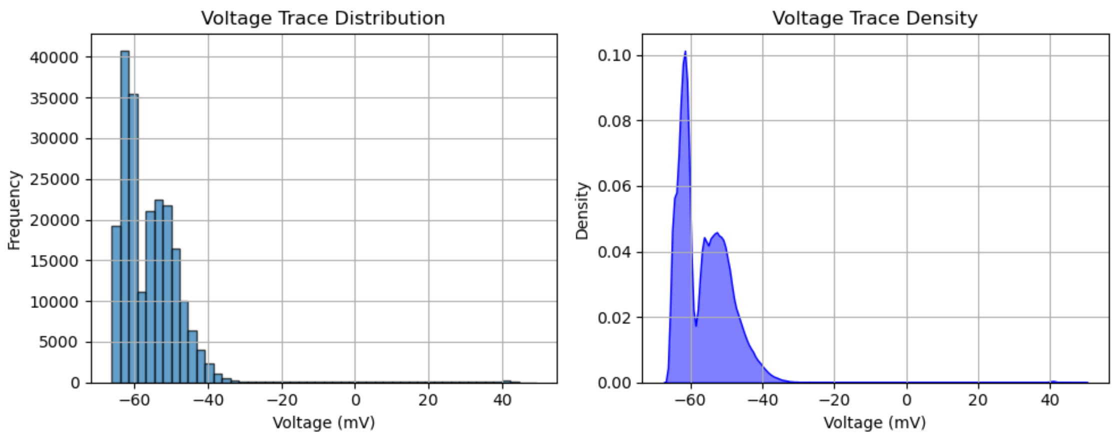
```
    Voltage Trace (mV): [-61.2   -60.856 -61.2   … -56.228 -56.196 -56.353]
    Command Input (mV): [0. 0. 0. … 0. 0. 0.]
     Recorded Channels: ['Waveform']
      Command Channels: ['AO #0']
```

2.5.2 Exploring all sweeps of an abf file

[7]:
```
import numpy as np

import matplotlib.pyplot as plt
data = abf.sweepY  # The voltage trace

stats = {
    "Mean (mV)": np.mean(data),
    "Median (mV)": np.median(data),
    "Min (mV)": np.min(data),
    "Max (mV)": np.max(data),
    "Std Dev (mV)": np.std(data),
    "Range (mV)": np.ptp(data),  # Max - Min
}

print("\nVoltage Trace Statistics:")
for key, value in stats.items():
    print(f"{key:>20}: {value:.3f}")


import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Create a figure with two subplots (1 row, 2 columns)
fig, axes = plt.subplots(1, 2, figsize=(10, 4))

# Plot histogram on the first subplot
axes[0].hist(data, bins=50, edgecolor='black', alpha=0.7)
axes[0].set_xlabel("Voltage (mV)")
axes[0].set_ylabel("Frequency")
axes[0].set_title("Voltage Trace Distribution")
axes[0].grid(True)

# Plot KDE on the second subplot
sns.kdeplot(data, bw_adjust=0.5, fill=True, color="b", alpha=0.5, ax=axes[1])
axes[1].set_xlabel("Voltage (mV)")
axes[1].set_ylabel("Density")
axes[1].set_title("Voltage Trace Density")
```

```
axes[1].grid(True)

# Adjust layout
plt.tight_layout()
plt.show()
```

```
Voltage Trace Statistics:
           Mean (mV): -55.656
         Median (mV): -56.853
            Min (mV): -66.204
            Max (mV): 49.191
        Std Dev (mV): 9.172
          Range (mV): 115.395
```

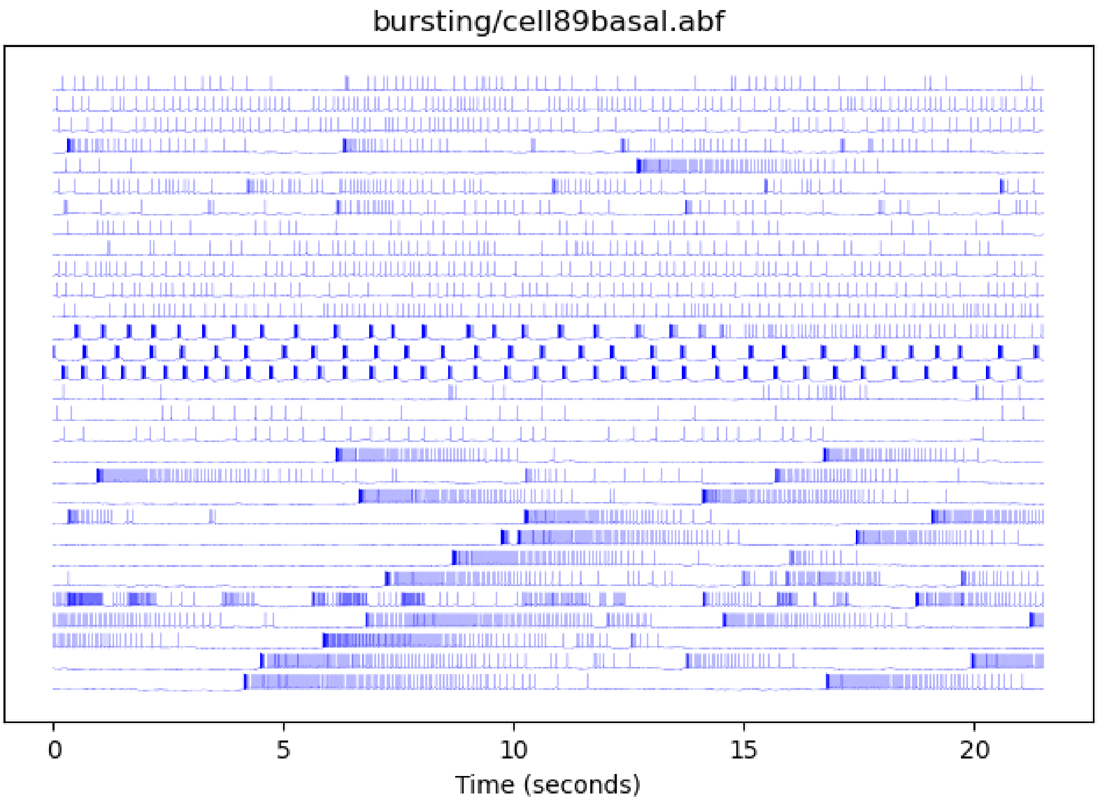


Of course, the previous plots are not particularly interesting, as they represent the distribution of the signal while mixing both inter-burst and burst phases. A more insightful approach would be to plot the distributions separately: one for the inter-burst signal and another for the intra-burst signal. Note that the previous plots exhibit a bimodal distribution, which is certainly related to the two phases of the signal—burst and non-burst (quiescent or background activity).

[8]:
```
def plot_abf():
    plt.figure(figsize=(8, 5))

    # plot every sweep (with vertical offset)
    for sweepNumber in abf.sweepList:
        abf.setSweep(sweepNumber)
        offset = 140*sweepNumber
        plt.plot(abf.sweepX, abf.sweepY+offset, color='b',lw=0.1)

    # decorate the plot
    plt.gca().get_yaxis().set_visible(False)  # hide Y axis
```

```
    plt.title(file_path)
    plt.xlabel(abf.sweepLabelX)
    plt.show()
```

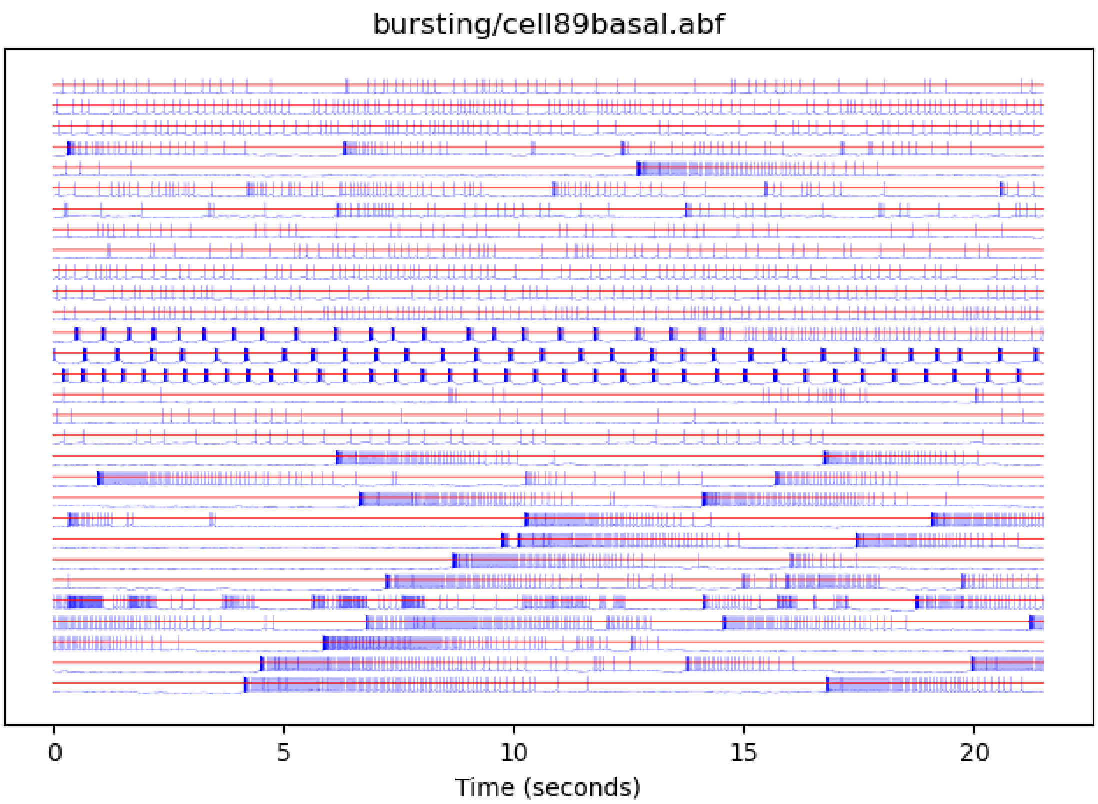
[9]:
```
plot_abf()
```



[10]:
```
import pyabf  # Load pyABF
import matplotlib.pyplot as plt

file_path = "bursting/cell89basal.abf"  # Select the ABF file
abf = pyabf.ABF(file_path)  # Load it
print(abf)  # Record characteristics

def plot_abf():
    plt.figure(figsize=(8, 5))

    # Plot every sweep with vertical offset
    for sweepNumber in abf.sweepList:
        abf.setSweep(sweepNumber)
        offset = 140 * sweepNumber
```

```
        plt.plot(abf.sweepX, abf.sweepY + offset, color='b', lw=0.1)  #␣
↪Recorded voltage
        plt.plot(abf.sweepX, abf.sweepC + offset, color='r', lw=0.5)  # Command␣
↪waveform in red

    # Decorate the plot
    plt.gca().get_yaxis().set_visible(False)  # Hide Y axis
    plt.title(file_path)
    plt.xlabel(abf.sweepLabelX)
    plt.show()

plot_abf()
```

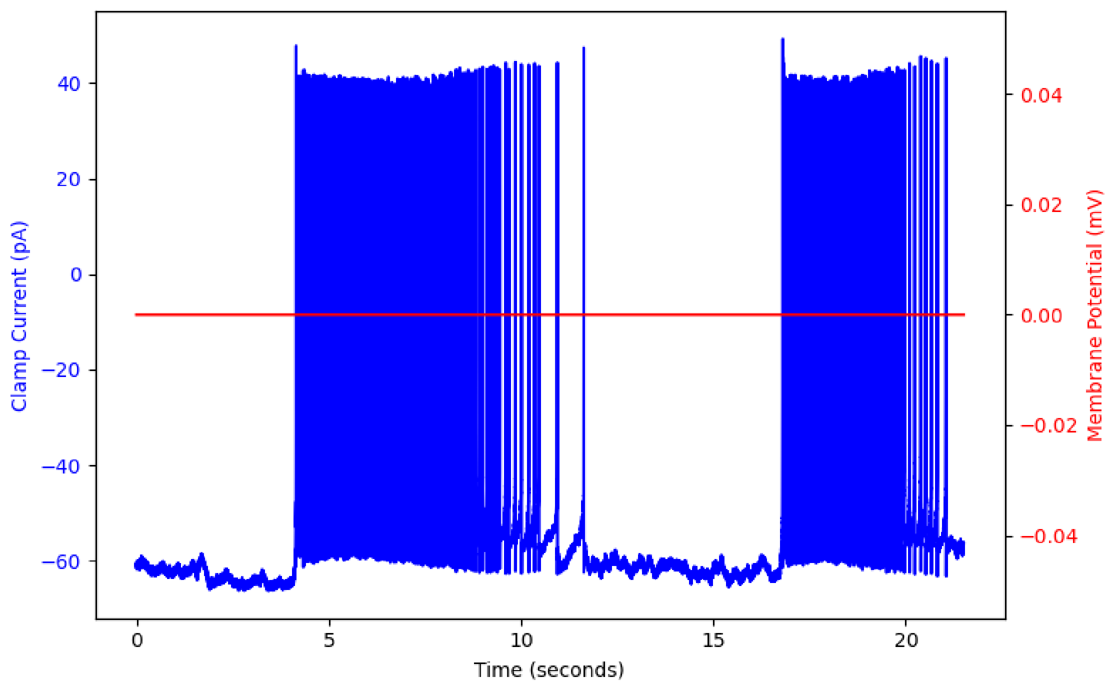
```
ABF (v2.6) with 1 channel (pA), sampled at 10.0 kHz, containing 30 sweeps,
having no tags, with a total length of 11.11 minutes, recorded without a
protocol file.
```



[11]:
```
import pyabf  # Load pyABF
import matplotlib.pyplot as plt

file_path = "bursting/cell89basal.abf"  # Select the ABF file
```

```python
abf = pyabf.ABF(file_path)  # Load it
print(abf)  # Record characteristics


# Créer la figure
fig, ax1 = plt.subplots(figsize=(8, 5))

# Tracer la courbe enregistrée (ADC) sur l'axe de gauche
ax1.plot(abf.sweepX, abf.sweepY, color='b', label="ADC waveform")
ax1.set_xlabel(abf.sweepLabelX)
ax1.set_ylabel(abf.sweepLabelY, color='b')
ax1.tick_params(axis='y', labelcolor='b')

# Créer un second axe y pour la courbe de commande (DAC)
ax2 = ax1.twinx()
ax2.plot(abf.sweepX, abf.sweepC, color='r', label="DAC waveform")
ax2.set_ylabel(abf.sweepLabelC, color='r')
ax2.tick_params(axis='y', labelcolor='r')

# Améliorer la mise en page
fig.tight_layout()
plt.show()
```

```
ABF (v2.6) with 1 channel (pA), sampled at 10.0 kHz, containing 30 sweeps,
having no tags, with a total length of 11.11 minutes, recorded without a
protocol file.
```



---

3 Spike detection

I build on the ideas developed by David spikesandbursts:

> "I have utilized the function FindPeaks to analyze postsynaptic events (see post), and here I show you a simplified version to detect action potentials. For a more detailed analysis of action potentials, I recommend using the packages IPFX or EFEL (tutorials here). If you have already done the spike analysis, skip this part."

3.1 Python libraries

[17]:
```
import numpy as np
import pandas as pd

import pyabf

import scipy
from scipy import signal
from scipy.signal import find_peaks
from scipy.optimize import curve_fit
from scipy.stats import skew, kurtosis

import matplotlib.pyplot as plt
```

3.2 Load the data

[20]:
```
# ABF files
data = file_path
abf = pyabf.ABF(data)
print(abf)
```

```
ABF (v2.6) with 1 channel (pA), sampled at 10.0 kHz, containing 30 sweeps,
having no tags, with a total length of 11.11 minutes, recorded without a
protocol file.
```

3.3 Pre-process the signal: filtering

"I did not use it for this tutorial, but here is an example of how to filter the signal. More details can be found in this post."

[21]:
```
# Sampling rate
fs = int(abf.dataPointsPerMs * 1000)

# Lowpass Bessel filter
b_lowpass, a_lowpass = signal.bessel(4,     # Order of the filter
```

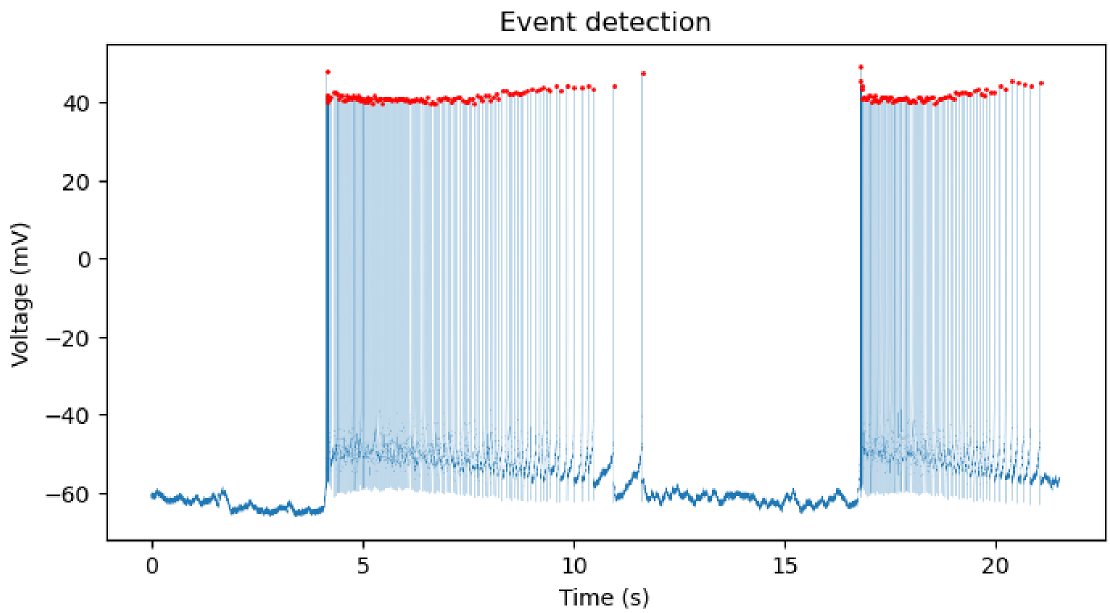
```
                                          2000,  # Cutoff frequency
                                          'low', # Type of filter
                                          analog=False,  # Analog or digital filter
                                          norm='phase',  # Critical frequency␣
 ↪normalization
                                          fs=fs)  # fs: sampling frequency

signal_filtered = signal.filtfilt(b_lowpass, a_lowpass, abf.sweepY)
```

3.4 Action potentials detection: FindPeaks

"I have utilized the function FindPeaks to analyze postsynaptic events (see post), and here I show you a simplified version to detect action potentials. For a more detailed analysis of action potentials, I recommend using the packages IPFX or EFEL (tutorials here). If you have already done the spike analysis, skip this part."

[22]:
```
# Assign the variables here to simplify the code
time = abf.sweepX
peaks_signal = abf.sweepY  # Or signal_filtered
abf.setSweep(15)

# Set parameters for the Find peaks function (set to None if not needed)
thresh_min = -25                     # Min threshold to detect spikes
thresh_prominence = 15               # Min spike amplitude
thresh_min_width = 0.5 * (fs/1000)  # Min required width in ms
distance_min = 1 * (fs/1000)        # Min horizontal distance between peaks
pretrigger_window = (1.5 * fs)/1000
posttrigger_window = (2 * fs)/1000

# Find peaks function
peaks, peaks_dict = find_peaks(peaks_signal,
           height=thresh_min,
           threshold=thresh_min,
           distance=distance_min,
           prominence=thresh_prominence,
           width=thresh_min_width,
           wlen=None,       # Window length to calculate prominence
           rel_height=0.5,  # Relative height at which the peak width is␣
 ↪measured
           plateau_size=None)

# Create table with results
spikes_table = pd.DataFrame(columns = ['spike', 'spike_index', 'spike_time',
                                        'inst_freq', 'isi_s',
                                        'width', 'rise_half_ms', 'decay_half_ms',
                                        'spike_peak', 'spike_amplitude'])
```

```
spikes_table.spike = np.arange(1, len(peaks) + 1)
spikes_table.spike_index = peaks
spikes_table.spike_time = peaks / fs  # Divided by fs to get s
spikes_table.isi_s = np.diff(peaks, axis=0, prepend=peaks[0]) / fs
spikes_table.inst_freq = 1 / spikes_table.isi_s
spikes_table.width = peaks_dict['widths']/(fs/1000) # Width (ms) at half-height
spikes_table.rise_half_ms = (peaks - peaks_dict['left_ips'])/(fs/1000)
spikes_table.decay_half_ms = (peaks_dict['right_ips'] - peaks)/(fs/1000)
spikes_table.spike_peak = peaks_dict['peak_heights']  # height parameter is␣
 ↪needed
spikes_table.spike_amplitude = peaks_dict['prominences']  # prominence␣
 ↪parameter is needed

# Plot the detected spikes in the trace
fig, ax = plt.subplots(figsize=(8, 4))
ax.plot(time, peaks_signal,lw=0.1)

# Red dot on each detected spike
ax.plot(peaks/fs, peaks_signal[peaks], "r.",markersize=2)

# Add a number to each detected peak
# for i, txt in enumerate(spikes_table.spike):
#     ax1.annotate(spikes_table.spike[i], (peaks[i]/fs, peaks_signal[peaks][i]))

ax.set_title("Event detection")
ax.set_xlabel("Time (s)")
ax.set_ylabel("Voltage (mV)")
#ax.axes.set_xlim(0.4, 0.9)  # Zoom in the trace

# Show graph and table
plt.show()
spikes_table
```



[22]:

	spike	spike_index	spike_time	inst_freq	isi_s	width	\
0	1	41492	4.1492	inf	0.0000	0.530190	
1	2	41545	4.1545	188.679245	0.0053	0.535173	
2	3	41605	4.1605	166.666667	0.0060	0.553585	
3	4	41672	4.1672	149.253731	0.0067	0.578264	
4	5	41757	4.1757	117.647059	0.0085	0.595801	
..	…	…	…	…	…	…	
196	197	203824	20.3824	6.531679	0.1531	0.618372	
197	198	205210	20.5210	7.215007	0.1386	0.615512	
198	199	206622	20.6622	7.082153	0.1412	0.627193	
199	200	208157	20.8157	6.514658	0.1535	0.621055	
200	201	210475	21.0475	4.314064	0.2318	0.614413	

	rise_half_ms	decay_half_ms	spike_peak	spike_amplitude
0	0.099506	0.430684	47.752998	113.268997
1	0.198077	0.337096	41.466999	100.508999
2	0.194615	0.358971	40.966999	98.790001
3	0.185913	0.392351	41.623001	100.822002
4	0.204363	0.391437	40.028999	97.350998
..	…	…	…	…
196	0.171005	0.447368	45.533001	108.327999
197	0.185775	0.429737	45.063000	107.201000
198	0.225217	0.401976	44.563000	107.357998
199	0.147202	0.473853	44.000000	106.638000
200	0.147189	0.467223	45.063000	108.232998

```
[201 rows x 10 columns]
```

3.5 Export the table and the plot

Documentation: save the figure, and table to csv.

[23]:
```
fig.savefig('bursting/cell89basal.png', dpi=300)
spikes_table.to_csv('bursting/cell89basal_spike_table.csv', index=False)
```

3.6 Interspike Intervals

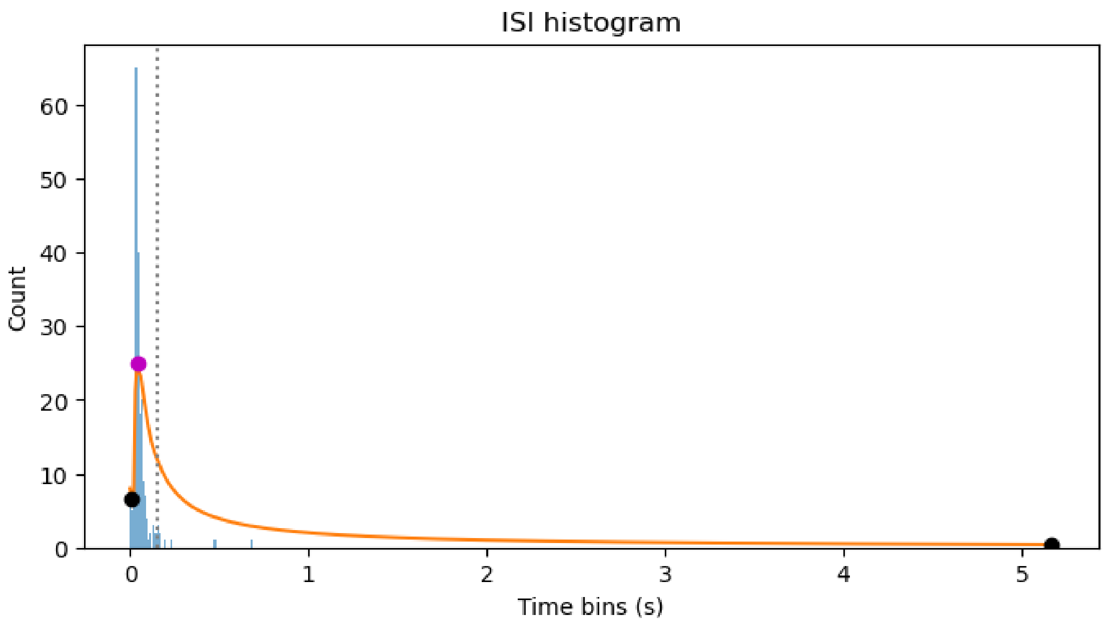
Next, the histogram of interspike intervals (ISI) helps choose reliable threshold parameters in burst analysis. If you already have a table with the action potential results, load the ISIs data into the variable `hist_data`.

The code below will plot the histogram and calculate some distribution statistics. Additionally, I have simplified the cumulative moving average (Kapucu et al., 2012) to find peaks and valleys. - Skewness quantifies distribution symmetry: 0 (symmetrical), positive (longer right tail), negative (longer left tail). Rule of thumb: skew > 1 or <-1 means significant. - Kurtosis quantifies tail similarity to the Gaussian distribution: 0 (Gaussian), negative (fewer tail values than Gaussian), positive (more tail values).

Of course, the ISI distribution of the pyloric dilator neuron has an ideal bimodal distribution, while the ISI distribution is noisier in other cases. This makes threshold calculations challenging and beyond the scope of this tutorial. However, if you are interested, explore burst detection algorithms using ISI in Pasquale et al., 2010, Kapucu et al., 2012, and Bakkum et al., 2014.

[24]:
```
# Assign ISI data to this variable
hist_data = spikes_table['isi_s']

# Empty DataFrame for histogram stats
hist_stats = pd.DataFrame()

# Bin size
bin_size = 10  # in miliseconds

# Histogram
isi_range = np.ptp(hist_data)
bins = int((isi_range * 1000 / bin_size) + 0.5)  # Round to the nearest integer
hist = np.histogram(hist_data, bins=bins)
hist_counts = hist[0]
hist_bins = hist[1]

# Cumulative moving average
cum = np.cumsum(hist_counts)  # Cumulative sum
cma = cum / np.arange(1, len(cum) + 1)

# Calculate peaks and valleys of the cma
cma_peaks_indexes = scipy.signal.argrelextrema(cma, np.greater)
```

```python
cma_valleys_indexes = scipy.signal.argrelextrema(cma, np.less)

# Select the peak you're interested in
peak_index = cma_peaks_indexes[0][0]  # Change second number to select the peak
alpha = cma[peak_index] * 0.5  # Half-peak, adapt the value to your threshold criterion

# Calculate cma_threshold_index relative to the selected cma_peak
cma_threshold = (np.argmin(cma[peak_index:] >= alpha) + peak_index) * bin_size/1000

# Dataframe with histogram statistics
length = len(hist_stats)
hist_stats.loc[length, 'mean_isi'] = np.mean(hist_data)
hist_stats.loc[length, 'median_isi'] = np.median(hist_data)
hist_stats.loc[length, 'kurtosis'] = kurtosis(hist_counts)
hist_stats.loc[length, 'skewness'] = skew(hist_counts, bias=True)
hist_stats.loc[length, 'cma_threshold'] = cma_threshold
hist_stats.loc[length, 'cma_valley_time'] = cma_valleys_indexes[0][1] * bin_size/1000  # Change peak index as needed
hist_stats.loc[length, 'cma_peak_time'] = cma_peaks_indexes[0][0] * bin_size/1000  # Change peak index as needed

# Plot ISI histogram
fig, ax = plt.subplots(figsize=(8, 4))
ax.set_title("ISI histogram")
ax.hist(hist_data, bins=bins, alpha=0.6)

# Plot CMA
cma_x = np.linspace(np.min(hist_bins), np.max(hist_bins), bins)
ax.plot(cma_x, cma)

# Plot CMA threshold line
ax.axvline(cma_threshold, linestyle="dotted", color="gray")

# Plot CMA valleys
ax.plot(cma_x[cma_valleys_indexes], cma[cma_valleys_indexes], 'ko')
ax.plot(cma_x[cma_peaks_indexes], cma[cma_peaks_indexes], 'mo')

# ax.set_xscale('log')  # Logarithmic scale may be easier to set the threshold
ax.set_xlabel("Time bins (s)")
ax.set_ylabel("Count")

# Show graph and table
plt.show()
hist_stats
```



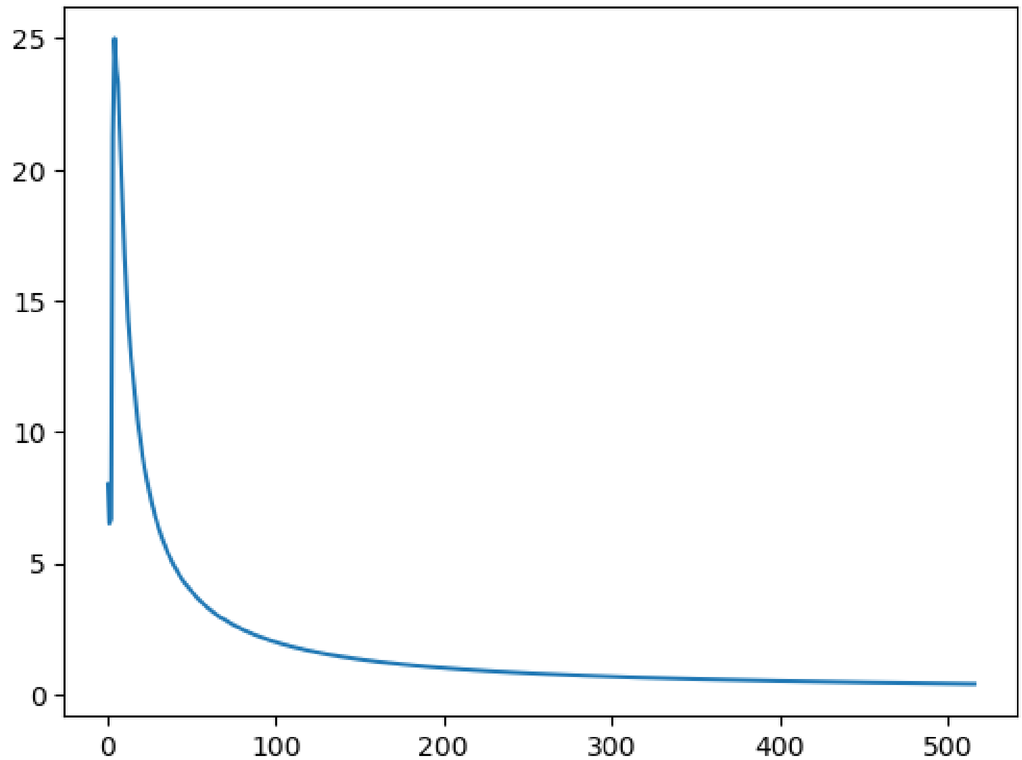
[24]:
```
   mean_isi  median_isi    kurtosis   skewness  cma_threshold  \
0  0.084071      0.0431  222.864529  14.087052           0.15

   cma_valley_time  cma_peak_time
0             5.15           0.04
```

Let's do something simpler:

[27]:
```
# Assign ISI data to this variable
hist_data = spikes_table['isi_s']

# Empty DataFrame for histogram stats
hist_stats = pd.DataFrame()

# Bin size
bin_size = 10  # in miliseconds

# Histogram
isi_range = np.ptp(hist_data)
bins = int((isi_range * 1000 / bin_size) + 0.5)  # Round to the nearest integer
hist = np.histogram(hist_data, bins=bins)
hist_counts = hist[0]
hist_bins = hist[1]

# Cumulative moving average
cum = np.cumsum(hist_counts)  # Cumulative sum
cma = cum / np.arange(1, len(cum) + 1)
```

```
plt.plot(cma)
```

[27]: [<matplotlib.lines.Line2D at 0x169c564f0>]



---

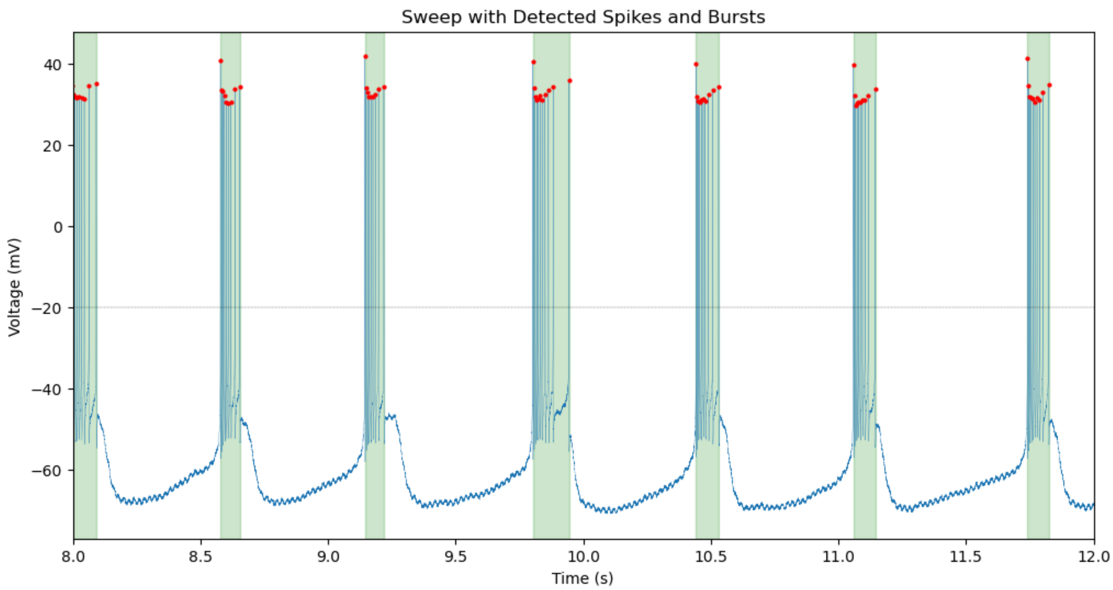
4 Burst detection

[30]:
```
import pyabf
import numpy as np
from scipy.signal import find_peaks
import matplotlib.pyplot as plt

abf = pyabf.ABF(file_path)
abf.setSweep(15)

# Extract sweep data
time = abf.sweepX  # Time axis for the sweep
voltage = abf.sweepY  # Voltage data for the sweep

# Detect spikes using a threshold or peak detection
```

```
threshold = -20  # Set your voltage threshold for spike detection (e.g., -20 mV)
spike_indices, _ = find_peaks(voltage, height=threshold)
```

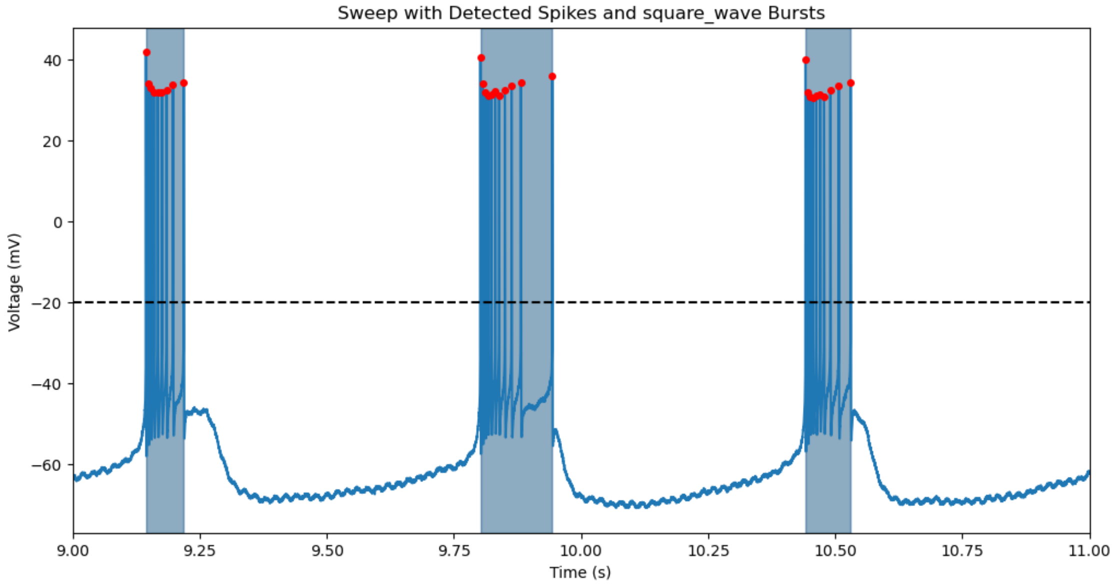
[31]:
```
# Detect spikes
threshold = -20  # Set your voltage threshold for spike detection (e.g., -20 mV)
spike_indices, _ = find_peaks(voltage, height=threshold)
spike_times = time[spike_indices]  # Convert spike indices to times

# Detect bursts based on ISI
isi = np.diff(spike_times)  # Inter-spike intervals
burst_threshold = 0.3  # Define an ISI threshold for bursts (e.g., 20 ms)

# Identify bursts
bursts = []
current_burst = [spike_times[0]]  # Initialize the first burst with the first␣
↪spike
for i in range(1, len(isi)):
    if isi[i - 1] < burst_threshold:  # Continue the burst
        current_burst.append(spike_times[i])
    else:  # End the current burst and start a new one
        if len(current_burst) > 1:  # Only consider bursts with more than 1␣
↪spike
            bursts.append((current_burst[0], current_burst[-1]))
        current_burst = [spike_times[i]]
# Add the last burst if valid
if len(current_burst) > 1:
    bursts.append((current_burst[0], current_burst[-1]))

# Plot the sweep, spikes, and bursts
plt.figure(figsize=(12, 6))
plt.plot(time, voltage, label='Sweep Data',lw=0.2)
plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',␣
↪markersize=4)

# Highlight bursts with shaded regions
for burst_start, burst_end in bursts:
    plt.axvspan(burst_start, burst_end, color='green', alpha=0.2, label='Burst')

plt.axhline(threshold, color='k', linestyle='--', label='Threshold',lw=0.2)
plt.xlabel("Time (s)")
plt.ylabel("Voltage (mV)")
plt.title("Sweep with Detected Spikes and Bursts")
plt.xlim((8,12))
#plt.legend()
plt.show()

# Print detected bursts
```

```
#for i, (burst_start, burst_end) in enumerate(bursts):
#     print(f"Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}␣
↪s")
```



[32]:
```
# Detect "square_wave" bursts
square_wave_bursts = []

for i, (burst_start, burst_end) in enumerate(bursts):
    # Calculate the mean voltage during the burst
    burst_mask = (time >= burst_start) & (time <= burst_end)
    burst_min_voltage = np.mean(voltage[burst_mask])

    # Calculate mean voltage during the preceding inter-burst interval
    if i > 0:  # Check if there's a previous burst
        prev_end = bursts[i - 1][1]
        inter_burst_prev_mask = (time > prev_end) & (time < burst_start)
        prev_mean_voltage = np.mean(voltage[inter_burst_prev_mask])
    else:
        prev_mean_voltage = float('-inf')  # No previous interval

    # Calculate mean voltage during the succeeding inter-burst interval
    if i < len(bursts) - 1:  # Check if there's a next burst
        next_start = bursts[i + 1][0]
        inter_burst_next_mask = (time > burst_end) & (time < next_start)
        next_mean_voltage = np.mean(voltage[inter_burst_next_mask])
    else:
        next_mean_voltage = float('-inf')  # No next interval
```

```
    # Test if the burst is "square_wave"
    if burst_min_voltage > prev_mean_voltage and burst_min_voltage >␣
↪next_mean_voltage:
        square_wave_bursts.append((burst_start, burst_end))

# Plot the sweep with square_wave bursts highlighted
plt.figure(figsize=(12, 6))
plt.plot(time, voltage, label='Sweep Data')
plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',␣
↪markersize=8)

# Highlight bursts
for burst_start, burst_end in bursts:
    plt.axvspan(burst_start, burst_end, color='green', alpha=0.3, label='Burst')

# Highlight square_wave bursts
for burst_start, burst_end in square_wave_bursts:
    plt.axvspan(burst_start, burst_end, color='blue', alpha=0.2,␣
↪label='square_wave Burst')

plt.axhline(threshold, color='k', linestyle='--', label='Threshold')
plt.xlabel("Time (s)")
plt.ylabel("Voltage (mV)")
plt.title("Sweep with Detected Spikes and square_wave Bursts")
#plt.legend()
plt.xlim((9,11))
plt.show()

# Print results
#for i, (burst_start, burst_end) in enumerate(square_wave_bursts):
#    print(f"square_wave Burst {i + 1}: Start = {burst_start:.3f} s, End =␣
↪{burst_end:.3f} s")
```



[34]:
```
sweep_number = 9
abf = pyabf.ABF(file_path)
abf.setSweep(sweep_number)

# Extract sweep data
time = abf.sweepX  # Time axis for the sweep
voltage = abf.sweepY  # Voltage data for the sweep

# Detect spikes
threshold = -20  # Set your voltage threshold for spike detection (e.g., -20 mV)
spike_indices, _ = find_peaks(voltage, height=threshold)
spike_times = time[spike_indices]  # Convert spike indices to times

# Detect bursts based on ISI
isi = np.diff(spike_times)  # Inter-spike intervals
burst_threshold = 0.3  # Define an ISI threshold for bursts (e.g., 20 ms)

# Identify bursts
bursts = []
current_burst = [spike_times[0]]  # Initialize the first burst with the first␣
↪spike
for i in range(1, len(isi)):
    if isi[i - 1] < burst_threshold:  # Continue the burst
        current_burst.append(spike_times[i])
    else:  # End the current burst and start a new one
        if len(current_burst) > 1:  # Only consider bursts with more than 1␣
↪spike
```

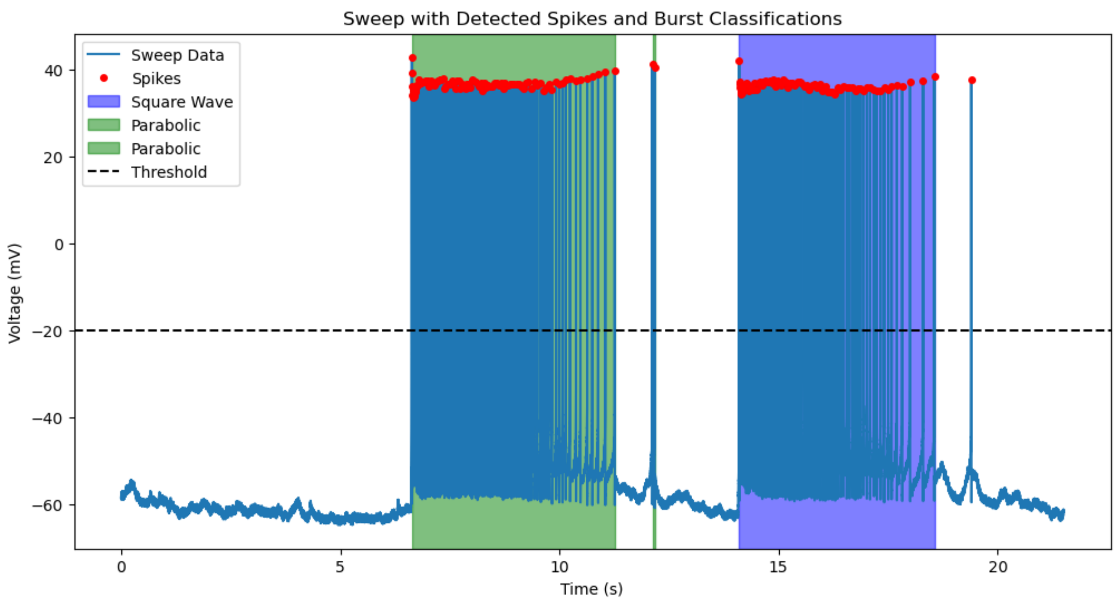
```
            bursts.append((current_burst[0], current_burst[-1]))
        current_burst = [spike_times[i]]
# Add the last burst if valid
if len(current_burst) > 1:
    bursts.append((current_burst[0], current_burst[-1]))

# Plot the sweep, spikes, and bursts
plt.figure(figsize=(12, 6))
plt.plot(time, voltage, label='Sweep Data',lw=0.2)
plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',␣
↪markersize=4)

# Highlight bursts with shaded regions
for burst_start, burst_end in bursts:
    plt.axvspan(burst_start, burst_end, color='green', alpha=0.2, label='Burst')

plt.axhline(threshold, color='k', linestyle='--', label='Threshold',lw=0.2)
plt.xlabel("Time (s)")
plt.ylabel("Voltage (mV)")
plt.title("Sweep with Detected Spikes and Bursts")
#plt.xlim((8,12))
#plt.legend()
plt.show()

# Print detected bursts
#for i, (burst_start, burst_end) in enumerate(bursts):
#    print(f"Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}␣
↪s")
```

---

5 Burst classification (very preliminary)

[35]:
```
# Initialize lists for categorized bursts
square_wave_bursts = []
parabolic_bursts = []
other_bursts = []

for i, (burst_start, burst_end) in enumerate(bursts):
    # Calculate the minimum voltage during the burst
    burst_mask = (time >= burst_start) & (time <= burst_end)
    burst_min_voltage = np.min(voltage[burst_mask])

    # Calculate mean voltage during the preceding inter-burst interval
    if i > 0:  # Check if there's a previous burst
        prev_end = bursts[i - 1][1]
        inter_burst_prev_mask = (time > prev_end) & (time < burst_start)
        prev_mean_voltage = np.mean(voltage[inter_burst_prev_mask])
    else:
        prev_mean_voltage = float('nan')  # No previous interval, ignore in␣
↪comparison

    # Calculate mean voltage during the succeeding inter-burst interval
    if i < len(bursts) - 1:  # Check if there's a next burst
        next_start = bursts[i + 1][0]
        inter_burst_next_mask = (time > burst_end) & (time < next_start)
        next_mean_voltage = np.mean(voltage[inter_burst_next_mask])
    else:
        next_mean_voltage = float('nan')  # No next interval, ignore in␣
↪comparison

    # Calculate overall inter-burst mean voltage
    inter_burst_mean = np.nanmean([prev_mean_voltage, next_mean_voltage])

    # Test conditions to classify the burst
    if burst_min_voltage > inter_burst_mean:
        square_wave_bursts.append((burst_start, burst_end))
    elif burst_min_voltage < inter_burst_mean:
        parabolic_bursts.append((burst_start, burst_end))
    else:
        other_bursts.append((burst_start, burst_end))

# Plot the sweep with classified bursts highlighted
plt.figure(figsize=(12, 6))
```

```python
plt.plot(time, voltage, label='Sweep Data')
plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',
 ↪markersize=8)

# Highlight bursts
for burst_start, burst_end in square_wave_bursts:
    plt.axvspan(burst_start, burst_end, color='blue', alpha=0.5, label='Square
 ↪Wave')

for burst_start, burst_end in parabolic_bursts:
    plt.axvspan(burst_start, burst_end, color='green', alpha=0.5,
 ↪label='Parabolic')

for burst_start, burst_end in other_bursts:
    plt.axvspan(burst_start, burst_end, color='orange', alpha=0.5,
 ↪label='Other')

plt.axhline(threshold, color='k', linestyle='--', label='Threshold')
plt.xlabel("Time (s)")
plt.ylabel("Voltage (mV)")
plt.title("Sweep with Detected Spikes and Burst Classifications")
plt.legend()
plt.show()

# Print results
print("Square Wave Bursts:")
for i, (burst_start, burst_end) in enumerate(square_wave_bursts):
    print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}
 ↪s")

print("\nParabolic Bursts:")
for i, (burst_start, burst_end) in enumerate(parabolic_bursts):
    print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}
 ↪s")

print("\nOther Bursts:")
for i, (burst_start, burst_end) in enumerate(other_bursts):
    print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}
 ↪s")
```

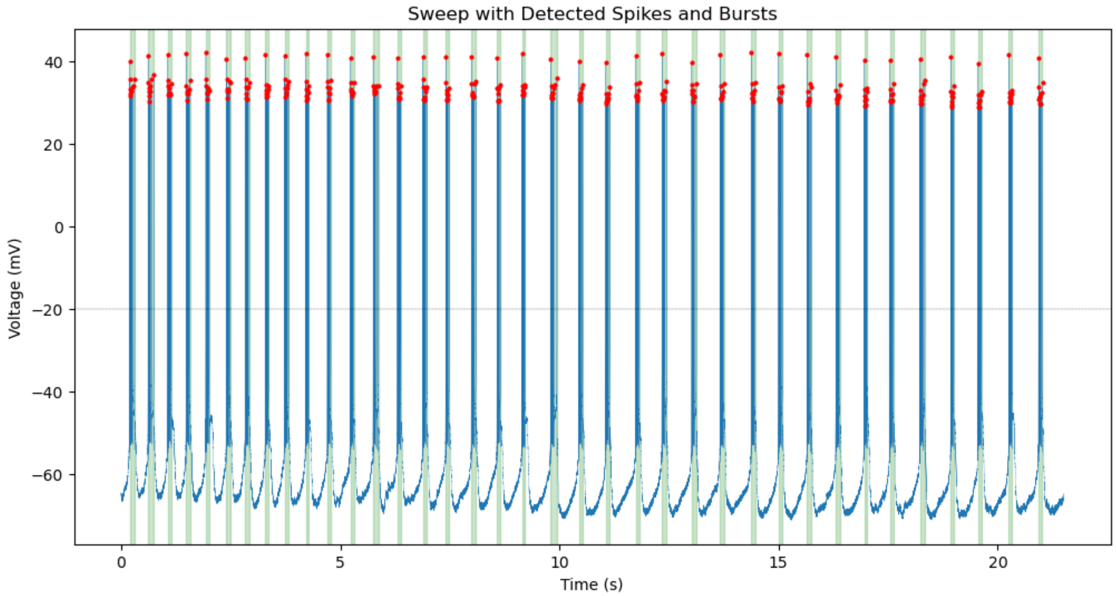



```
Square Wave Bursts:
  Burst 1: Start = 14.101 s, End = 18.554 s

Parabolic Bursts:
  Burst 1: Start = 6.633 s, End = 11.261 s
  Burst 2: Start = 12.119 s, End = 12.174 s

Other Bursts:
```

[37]:

```
sweep_number = 15
abf = pyabf.ABF(file_path)
abf.setSweep(sweep_number)

# Extract sweep data
time = abf.sweepX  # Time axis for the sweep
voltage = abf.sweepY  # Voltage data for the sweep

# Detect spikes
threshold = -20  # Set your voltage threshold for spike detection (e.g., -20 mV)
spike_indices, _ = find_peaks(voltage, height=threshold)
spike_times = time[spike_indices]  # Convert spike indices to times

# Detect bursts based on ISI
isi = np.diff(spike_times)  # Inter-spike intervals
burst_threshold = 0.3  # Define an ISI threshold for bursts (e.g., 20 ms)

# Identify bursts
```

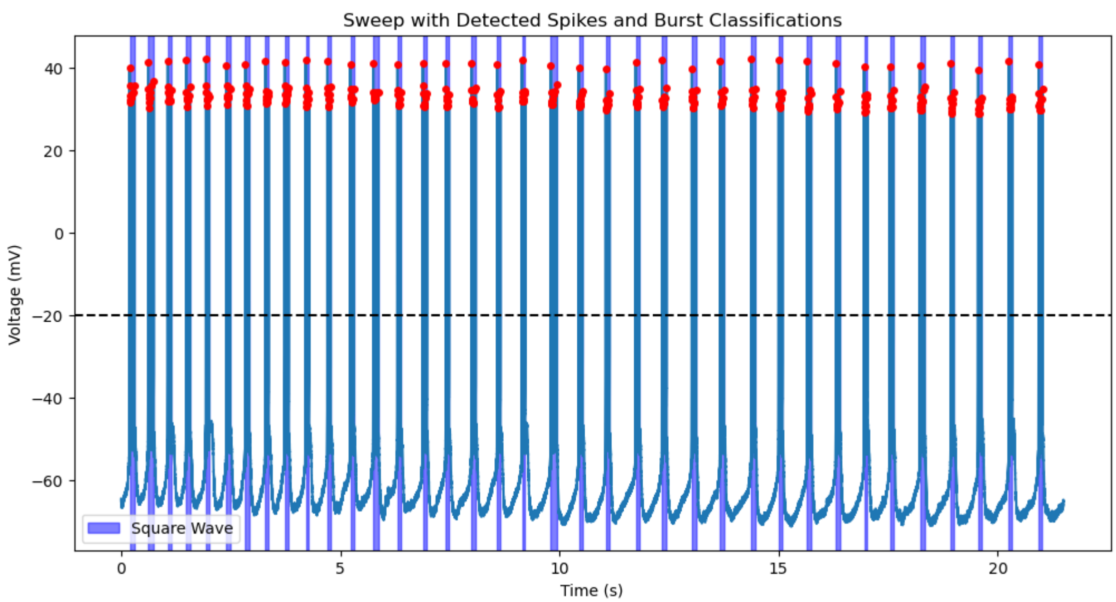
```
bursts = []
current_burst = [spike_times[0]]  # Initialize the first burst with the first␣
↪spike
for i in range(1, len(isi)):
    if isi[i - 1] < burst_threshold:  # Continue the burst
        current_burst.append(spike_times[i])
    else:  # End the current burst and start a new one
        if len(current_burst) > 1:  # Only consider bursts with more than 1␣
↪spike
            bursts.append((current_burst[0], current_burst[-1]))
        current_burst = [spike_times[i]]
# Add the last burst if valid
if len(current_burst) > 1:
    bursts.append((current_burst[0], current_burst[-1]))

# Plot the sweep, spikes, and bursts
plt.figure(figsize=(12, 6))
plt.plot(time, voltage, label='Sweep Data',lw=0.2)
plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',␣
↪markersize=4)

# Highlight bursts with shaded regions
for burst_start, burst_end in bursts:
    plt.axvspan(burst_start, burst_end, color='green', alpha=0.2, label='Burst')

plt.axhline(threshold, color='k', linestyle='--', label='Threshold',lw=0.2)
plt.xlabel("Time (s)")
plt.ylabel("Voltage (mV)")
plt.title("Sweep with Detected Spikes and Bursts")
#plt.xlim((8,12))
#plt.legend()
plt.show()
```



[38]:
```
# Initialize lists for categorized bursts
square_wave_bursts = []
parabolic_bursts = []
other_bursts = []

for i, (burst_start, burst_end) in enumerate(bursts):
    # Calculate the minimum voltage during the burst
    burst_mask = (time >= burst_start) & (time <= burst_end)
    burst_min_voltage = np.min(voltage[burst_mask])

    # Calculate mean voltage during the preceding inter-burst interval
    if i > 0:  # Check if there's a previous burst
        prev_end = bursts[i - 1][1]
        inter_burst_prev_mask = (time > prev_end) & (time < burst_start)
        prev_mean_voltage = np.mean(voltage[inter_burst_prev_mask])
    else:
        prev_mean_voltage = float('nan')  # No previous interval, ignore in␣
 ↪comparison

    # Calculate mean voltage during the succeeding inter-burst interval
    if i < len(bursts) - 1:  # Check if there's a next burst
        next_start = bursts[i + 1][0]
        inter_burst_next_mask = (time > burst_end) & (time < next_start)
        next_mean_voltage = np.mean(voltage[inter_burst_next_mask])
    else:
        next_mean_voltage = float('nan')  # No next interval, ignore in␣
 ↪comparison
```

```
    # Calculate overall inter-burst mean voltage
    inter_burst_mean = np.nanmean([prev_mean_voltage, next_mean_voltage])

    # Test conditions to classify the burst
    if burst_min_voltage > inter_burst_mean:
        square_wave_bursts.append((burst_start, burst_end))
    elif burst_min_voltage < inter_burst_mean:
        parabolic_bursts.append((burst_start, burst_end))
    else:
        other_bursts.append((burst_start, burst_end))

# Plot the sweep with classified bursts highlighted
plt.figure(figsize=(12, 6))
plt.plot(time, voltage, label='Sweep Data')
plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',␣
 ↪markersize=8)

# Highlight bursts with a single legend entry per category
square_wave_patch = None
parabolic_patch = None
other_patch = None

for burst_start, burst_end in square_wave_bursts:
    square_wave_patch = plt.axvspan(burst_start, burst_end, color='blue',␣
 ↪alpha=0.5, label='Square Wave')

for burst_start, burst_end in parabolic_bursts:
    parabolic_patch = plt.axvspan(burst_start, burst_end, color='green',␣
 ↪alpha=0.5, label='Parabolic')

for burst_start, burst_end in other_bursts:
    other_patch = plt.axvspan(burst_start, burst_end, color='orange', alpha=0.
 ↪5, label='Other')

# Filter out None handles
handles = [patch for patch in [square_wave_patch, parabolic_patch, other_patch]␣
 ↪if patch is not None]
labels = ['Square Wave', 'Parabolic', 'Other'][:len(handles)]

# Add a single legend entry for each classification
plt.legend(handles, labels)

plt.axhline(threshold, color='k', linestyle='--', label='Threshold')
plt.xlabel("Time (s)")
plt.ylabel("Voltage (mV)")
plt.title("Sweep with Detected Spikes and Burst Classifications")
```

```
plt.show()

# Print results
print("Square Wave Bursts:")
for i, (burst_start, burst_end) in enumerate(square_wave_bursts):
    print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}␣
↪s")

print("\nParabolic Bursts:")
for i, (burst_start, burst_end) in enumerate(parabolic_bursts):
    print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}␣
↪s")

print("\nOther Bursts:")
for i, (burst_start, burst_end) in enumerate(other_bursts):
    print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.3f}␣
↪s")
```




```
Square Wave Bursts:
  Burst 1: Start = 0.193 s, End = 0.307 s
  Burst 2: Start = 0.615 s, End = 0.744 s
  Burst 3: Start = 1.064 s, End = 1.145 s
  Burst 4: Start = 1.484 s, End = 1.574 s
  Burst 5: Start = 1.933 s, End = 2.010 s
  Burst 6: Start = 2.403 s, End = 2.491 s
  Burst 7: Start = 2.836 s, End = 2.925 s
  Burst 8: Start = 3.293 s, End = 3.367 s
```

```
Burst 9: Start = 3.733 s, End = 3.824 s
Burst 10: Start = 4.211 s, End = 4.286 s
Burst 11: Start = 4.705 s, End = 4.783 s
Burst 12: Start = 5.229 s, End = 5.306 s
Burst 13: Start = 5.751 s, End = 5.869 s
Burst 14: Start = 6.304 s, End = 6.382 s
Burst 15: Start = 6.883 s, End = 6.979 s
Burst 16: Start = 7.406 s, End = 7.483 s
Burst 17: Start = 7.993 s, End = 8.092 s
Burst 18: Start = 8.578 s, End = 8.654 s
Burst 19: Start = 9.144 s, End = 9.219 s
Burst 20: Start = 9.802 s, End = 9.944 s
Burst 21: Start = 10.442 s, End = 10.530 s
Burst 22: Start = 11.059 s, End = 11.144 s
Burst 23: Start = 11.740 s, End = 11.824 s
Burst 24: Start = 12.340 s, End = 12.444 s
Burst 25: Start = 13.019 s, End = 13.123 s
Burst 26: Start = 13.668 s, End = 13.754 s
Burst 27: Start = 14.379 s, End = 14.462 s
Burst 28: Start = 15.002 s, End = 15.090 s
Burst 29: Start = 15.654 s, End = 15.744 s
Burst 30: Start = 16.309 s, End = 16.399 s
Burst 31: Start = 16.951 s, End = 17.026 s
Burst 32: Start = 17.541 s, End = 17.625 s
Burst 33: Start = 18.226 s, End = 18.335 s
Burst 34: Start = 18.929 s, End = 18.998 s
Burst 35: Start = 19.553 s, End = 19.632 s
Burst 36: Start = 20.256 s, End = 20.330 s
Burst 37: Start = 20.933 s, End = 20.994 s

Parabolic Bursts:

Other Bursts:
```

[39]:

```python
def analyze_spikes_and_bursts(file_path, sweep_number, xmin=None, xmax=None,␣
↪voltage_threshold =None, burst_threshold=None):
    # Load the data
    abf = pyabf.ABF(file_path)
    abf.setSweep(sweep_number)
    time = abf.sweepX
    voltage = abf.sweepY

    #␣
↪---------------------------------------------------------------------------
    # --- Detect spikes␣
↪----------------------------------------------------------
```

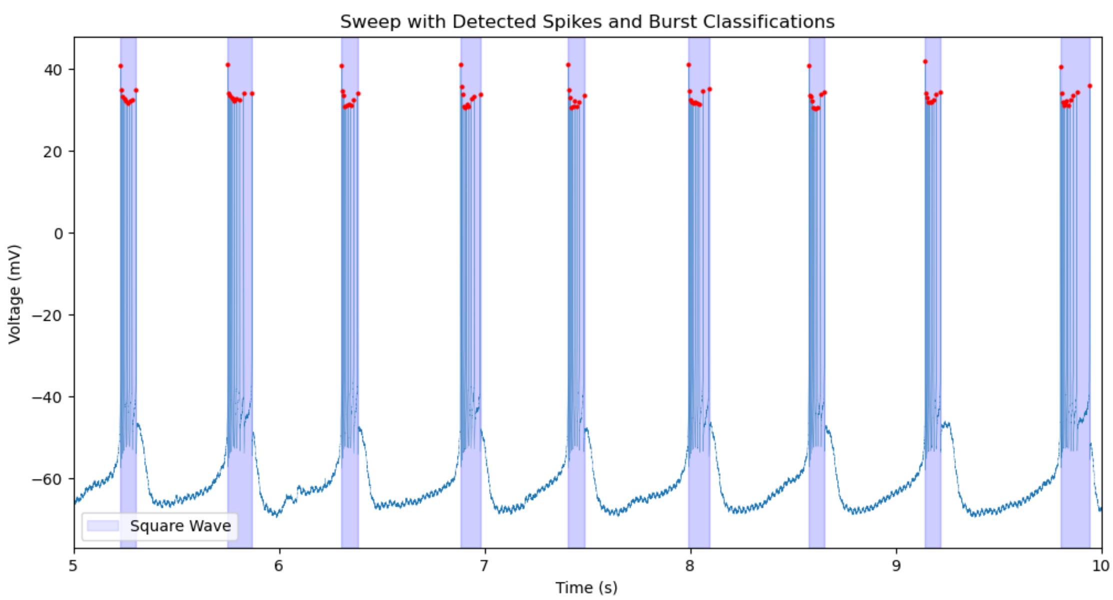
```
    #␣
↪-----------------------------------------------------------------------------

    spike_indices, _ = find_peaks(voltage, height=voltage_threshold)
    spike_times = time[spike_indices]  # Convert spike indices to times

    # Detect bursts based on ISI
    isi = np.diff(spike_times)  # Inter-spike intervals

    #␣
↪-----------------------------------------------------------------------------
    # --- Identify bursts
    #␣
↪-----------------------------------------------------------------------------

    bursts = []
    current_burst = [spike_times[0]]  # Initialize the 1st burst with the 1st␣
↪spike
    for i in range(1, len(isi)):
        if isi[i - 1] < burst_threshold:  # Continue the burst
            current_burst.append(spike_times[i])
        else:  # End the current burst and start a new one
            if len(current_burst) > 1:  # Only consider bursts with more than 1␣
↪spike
                bursts.append((current_burst[0], current_burst[-1]))
            current_burst = [spike_times[i]]
    # Add the last burst if valid
    if len(current_burst) > 1:
        bursts.append((current_burst[0], current_burst[-1]))

    #␣
↪-----------------------------------------------------------------------------
    # classify bursts
    #␣
↪-----------------------------------------------------------------------------

    square_wave_bursts = []
    parabolic_bursts = []
    other_bursts = []

    for i, (burst_start, burst_end) in enumerate(bursts):
        # Calculate the minimum voltage during the burst
        burst_mask = (time >= burst_start) & (time <= burst_end)
        burst_min_voltage = np.min(voltage[burst_mask])

        # Calculate mean voltage during the preceding inter-burst interval
```

```
        if i > 0:  # Check if there's a previous burst
            prev_end = bursts[i - 1][1]
            inter_burst_prev_mask = (time > prev_end) & (time < burst_start)
            prev_mean_voltage = np.mean(voltage[inter_burst_prev_mask])
        else:
            prev_mean_voltage = float('nan')  # No previous interval, ignore in␣
↪comparison

        # Calculate mean voltage during the succeeding inter-burst interval
        if i < len(bursts) - 1:  # Check if there's a next burst
            next_start = bursts[i + 1][0]
            inter_burst_next_mask = (time > burst_end) & (time < next_start)
            next_mean_voltage = np.mean(voltage[inter_burst_next_mask])
        else:
            next_mean_voltage = float('nan')  # No next interval, ignore in␣
↪comparison

        # Calculate overall inter-burst mean voltage
        inter_burst_mean = np.nanmean([prev_mean_voltage, next_mean_voltage])

        # Test conditions to classify the burst
        if burst_min_voltage > inter_burst_mean:
            square_wave_bursts.append((burst_start, burst_end))
        elif burst_min_voltage < inter_burst_mean:
            parabolic_bursts.append((burst_start, burst_end))
        else:
            other_bursts.append((burst_start, burst_end))

    #␣
↪-----------------------------------------------------------------------------
    # Plot
    #␣
↪-----------------------------------------------------------------------------

    # --- Plot the sweep with classified bursts highlighted
    plt.figure(figsize=(12, 6))
    plt.plot(time, voltage, label='Sweep Data',lw=0.2)
    plt.plot(time[spike_indices], voltage[spike_indices], 'r.', label='Spikes',␣
↪markersize=4)

    # Highlight bursts
    for burst_start, burst_end in square_wave_bursts:
        plt.axvspan(burst_start, burst_end, color='blue', alpha=0.1,␣
↪label='Square Wave')

    for burst_start, burst_end in parabolic_bursts:
```

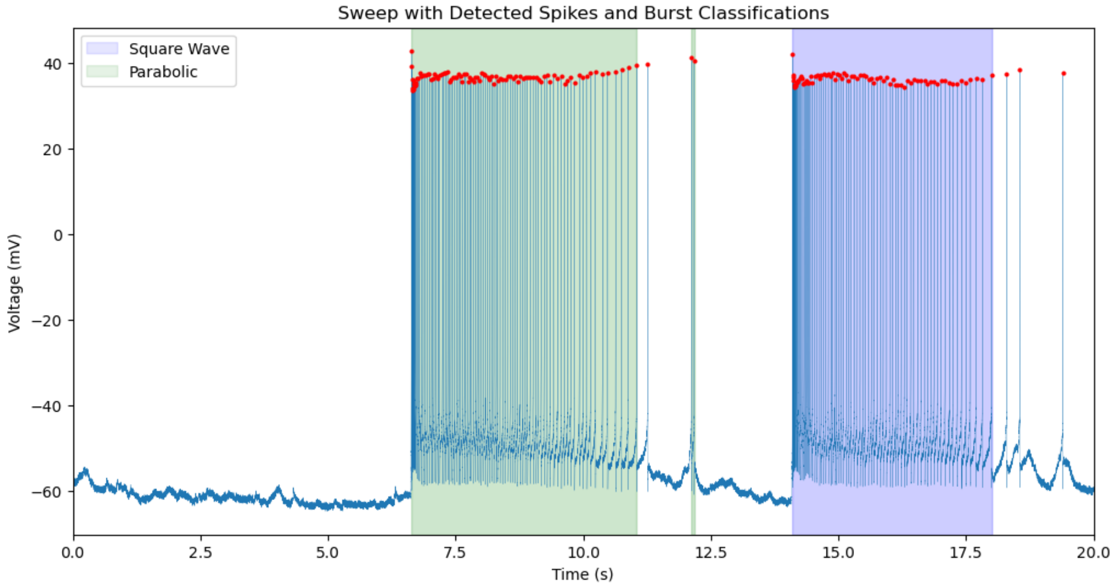
```
        plt.axvspan(burst_start, burst_end, color='green', alpha=0.1,␣
↪label='Parabolic')

    for burst_start, burst_end in other_bursts:
        plt.axvspan(burst_start, burst_end, color='orange', alpha=0.1,␣
↪label='Other')


    # Highlight bursts and prepare legend handles
    square_wave_patch = None
    parabolic_patch = None
    other_patch = None

    for burst_start, burst_end in square_wave_bursts:
        square_wave_patch = plt.axvspan(burst_start, burst_end, color='blue',␣
↪alpha=0.1, label='Square Wave')

    for burst_start, burst_end in parabolic_bursts:
        parabolic_patch = plt.axvspan(burst_start, burst_end, color='green',␣
↪alpha=0.1, label='Parabolic')

    for burst_start, burst_end in other_bursts:
        other_patch = plt.axvspan(burst_start, burst_end, color='orange',␣
↪alpha=0.1, label='Other')

    # Filter handles to include only non-None entries
    handles = []
    labels = []
    if square_wave_patch:
        handles.append(square_wave_patch)
        labels.append("Square Wave")
    if parabolic_patch:
        handles.append(parabolic_patch)
        labels.append("Parabolic")
    if other_patch:
        handles.append(other_patch)
        labels.append("Other")



    #plt.axhline(threshold, color='k', linestyle='--', label='Threshold')
    plt.xlabel("Time (s)")
    plt.ylabel("Voltage (mV)")
    plt.title("Sweep with Detected Spikes and Burst Classifications")
    plt.legend(handles, labels)
    plt.xlim((xmin,xmax))
    plt.show()
```

```
    # Print results
#   print("Square Wave Bursts:")
#   for i, (burst_start, burst_end) in enumerate(square_wave_bursts):
#       print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:.
↪3f} s")

#   print("\nParabolic Bursts:")
#   for i, (burst_start, burst_end) in enumerate(parabolic_bursts):
#       print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:
↪.3f} s")

#   print("\nOther Bursts:")
#   for i, (burst_start, burst_end) in enumerate(other_bursts):
#       print(f"  Burst {i + 1}: Start = {burst_start:.3f} s, End = {burst_end:
↪.3f} s")
# Example usage
# analyze_spikes_and_bursts("path_to_abf_file.abf", 15, xmin=0, xmax=10,␣
↪burst_threshold=50)
```

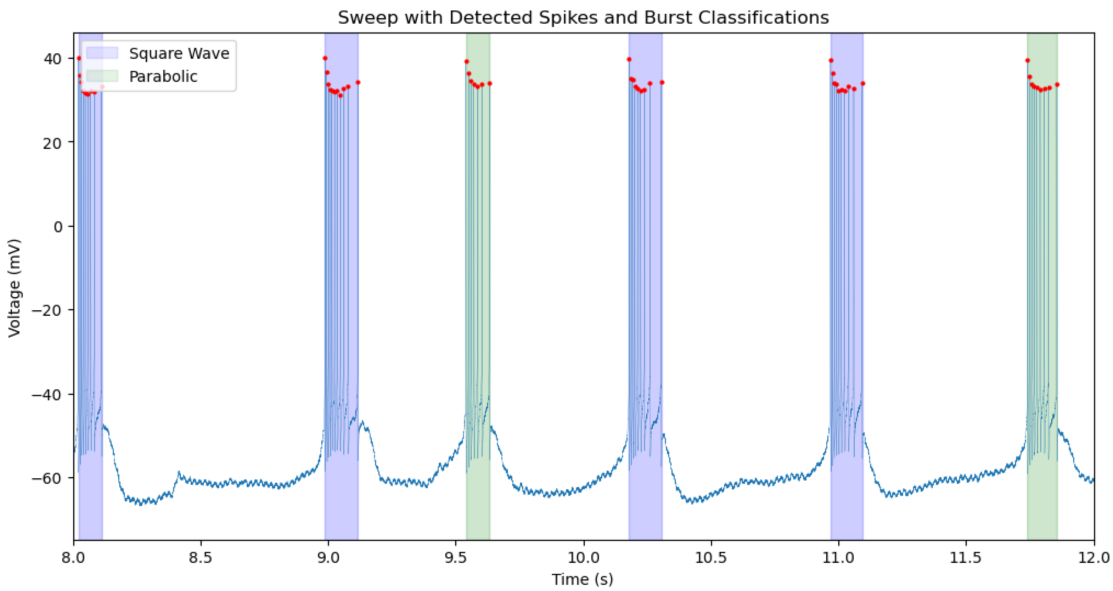
[40]:
```
sweep_number = 15
analyze_spikes_and_bursts(file_path, sweep_number, xmin=5, xmax=10,␣
↪voltage_threshold = -20, burst_threshold=0.3)
```



[41]:
```
sweep_number = 9
analyze_spikes_and_bursts(file_path, sweep_number, xmin=0, xmax=20,␣
↪voltage_threshold = -20, burst_threshold=0.2)
```



[42]:
```
sweep_number = 17
analyze_spikes_and_bursts(file_path, sweep_number, xmin=8, xmax=12,␣
↪voltage_threshold = -20, burst_threshold=0.1)
```



[ ]:
```

```