

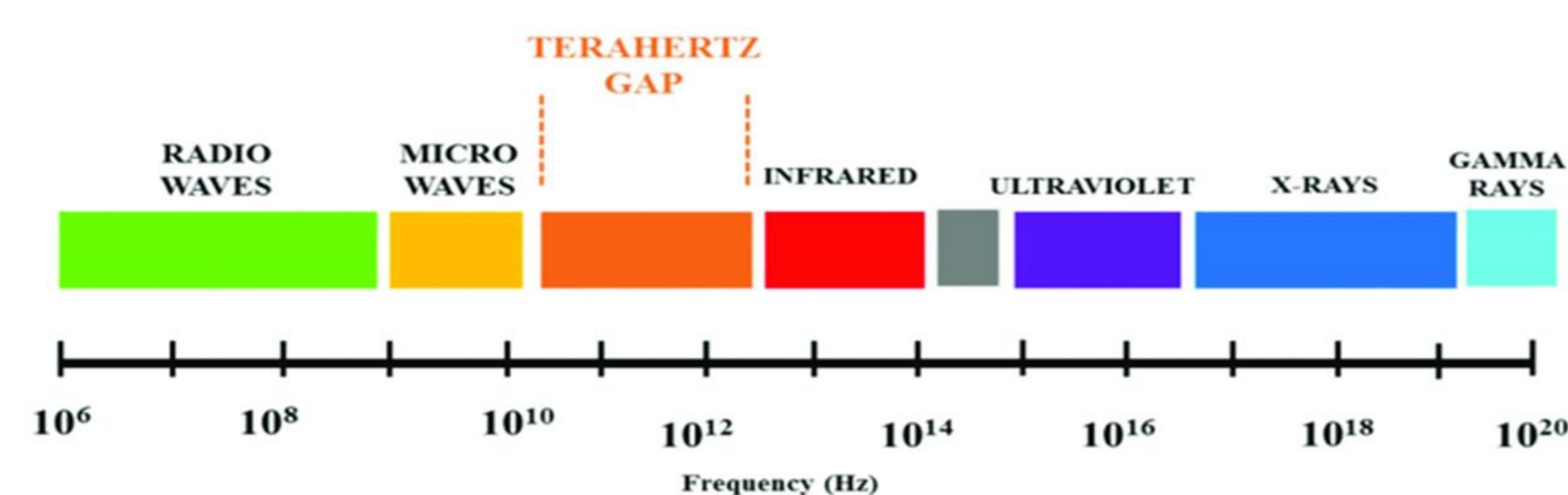
Abstract

- With the growing demand for high-speed data transfer, research into the terahertz (THz) band is more critical than ever.
- However, when considering the implications of this technology in the medical field, it is essential to understand the effect of THz radiation on the brain at the neuron level both to ensure safety of implantable devices as well as to explore potential therapeutic advantages.

Goal

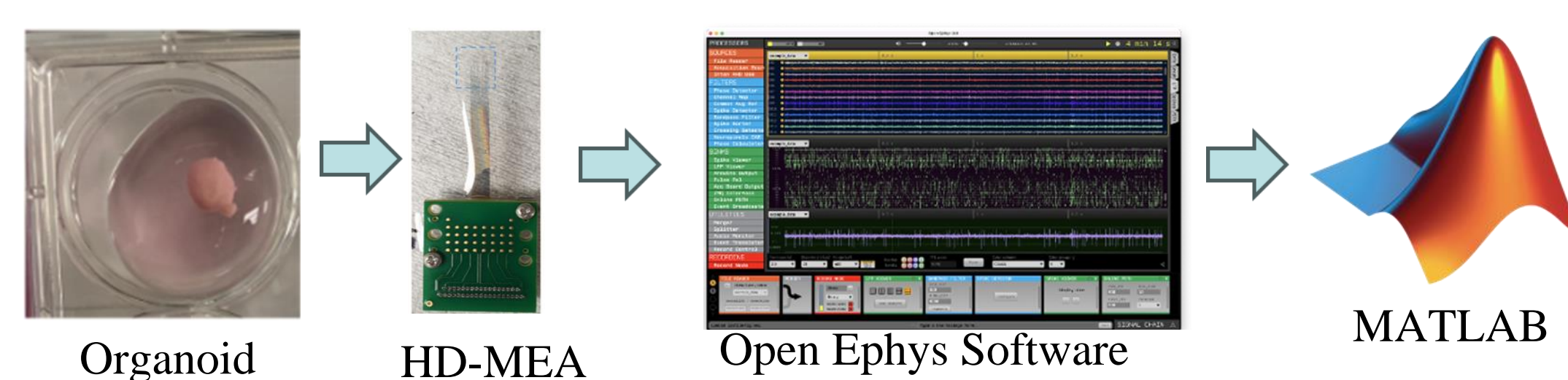
- To analyze neuronal activity in the presence of THz radiation by sorting data collected using a high-density multi-electrode array (HD-MEA) device and implementing appropriate spike sorting techniques.

Background



- Due to a lack of technology, the sub-band between microwaves and infrared remains underutilized.
- The THz gap has frequencies 0.1- 10THz, offering a wider bandwidth and high data speed.
- Terahertz radiation is highly absorbed by water which constitutes 80% of the human brain.

Methods



- Our data was collected from lab grown organoids that replicate brain tissue.
- The signals are detected by a High-density Multi-Electrode Array and sent to a signal processing software called Open Ephys.
- The data is then sent to MATLAB where we do our own processing.

Spike Sorting

1. Filtering

- Neurons send out electrical signals within the range of 300Hz to 3000Hz.
- We run the data through a bandpass filter in order to filter out all the signals outside of this range.

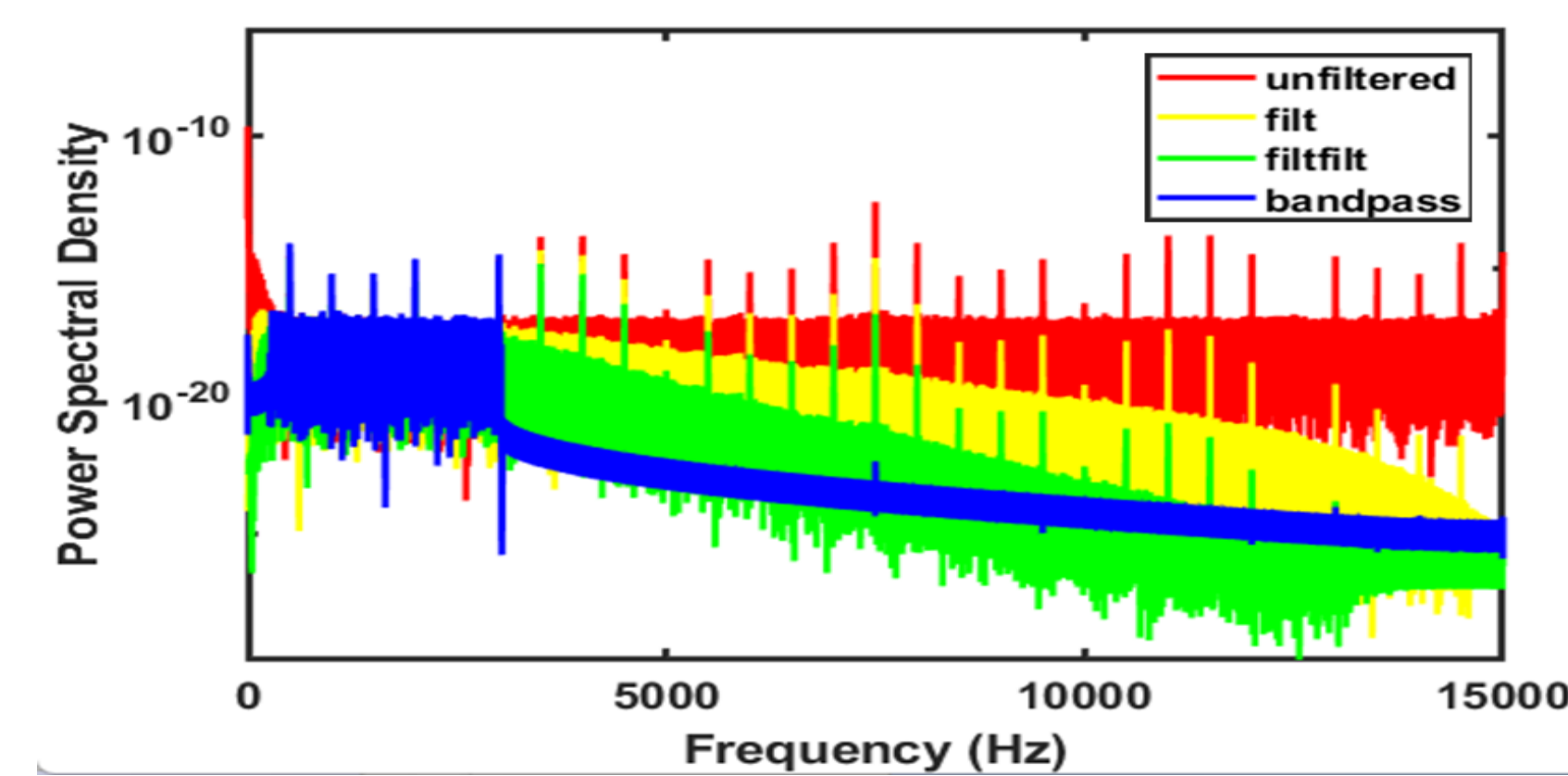


Figure 1: Comparison of bandpass filters

3. Spike Detection

- We set a threshold to detect neuron signals (spikes) in the data.
- $Threshold = 5 * median\{|S_{raw}|\}_{0.6745}$

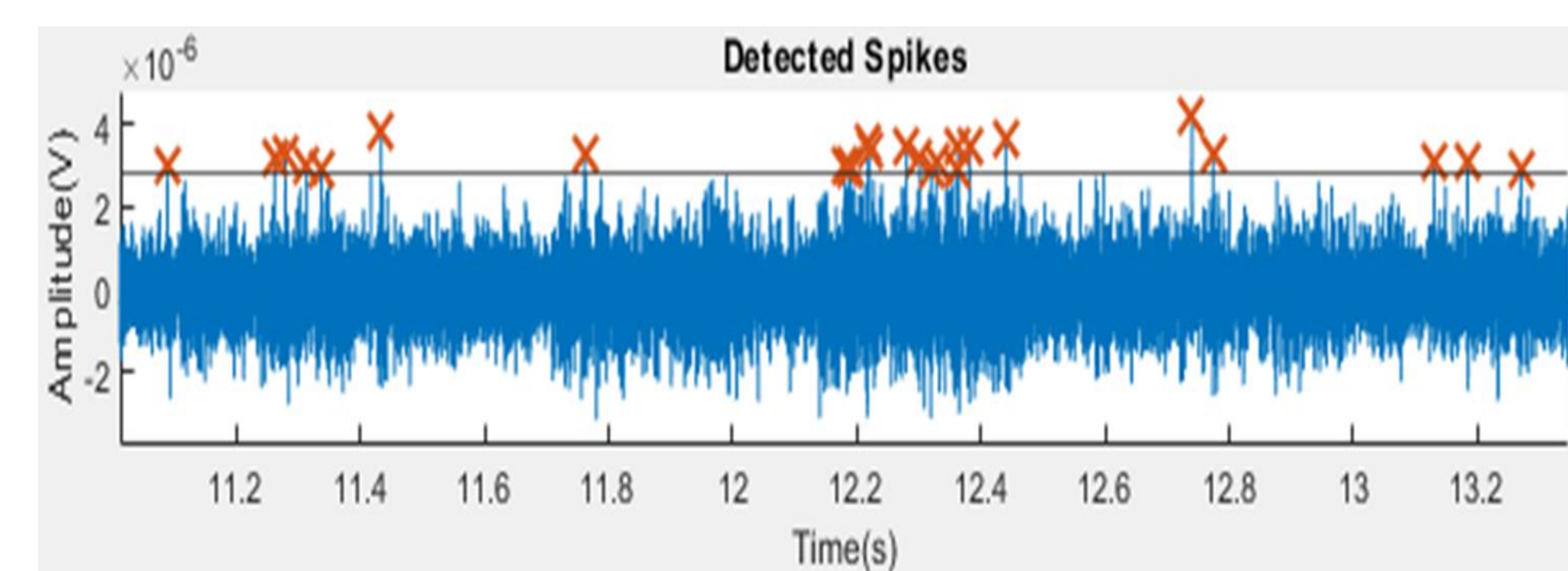


Figure 3: Spikes Detected above the Threshold

5. Feature Extraction

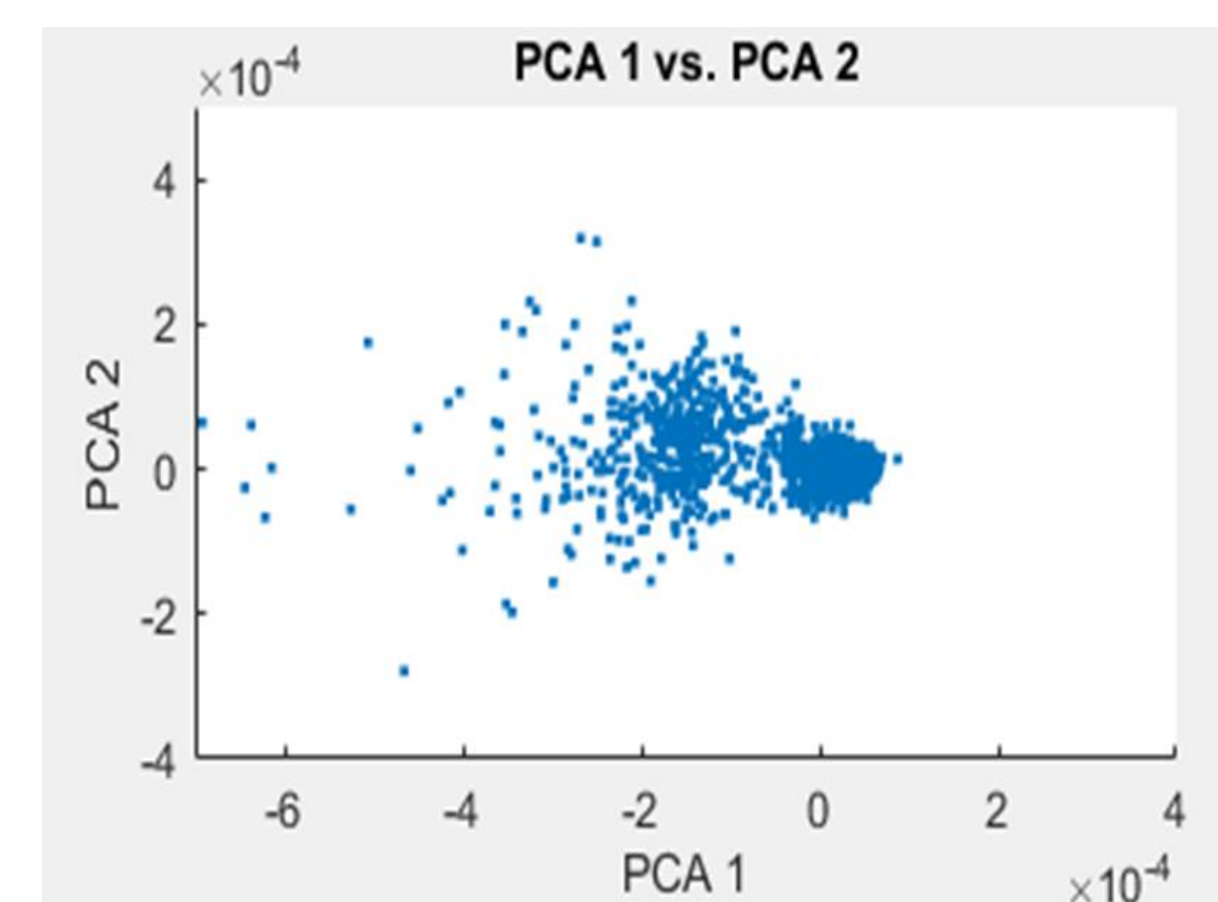


Figure 5: Principal Component Analysis

- Features are calculated from the spikes using Principal Component Analysis (PCA).
- Each point is representative of a spike.

2. Denoising

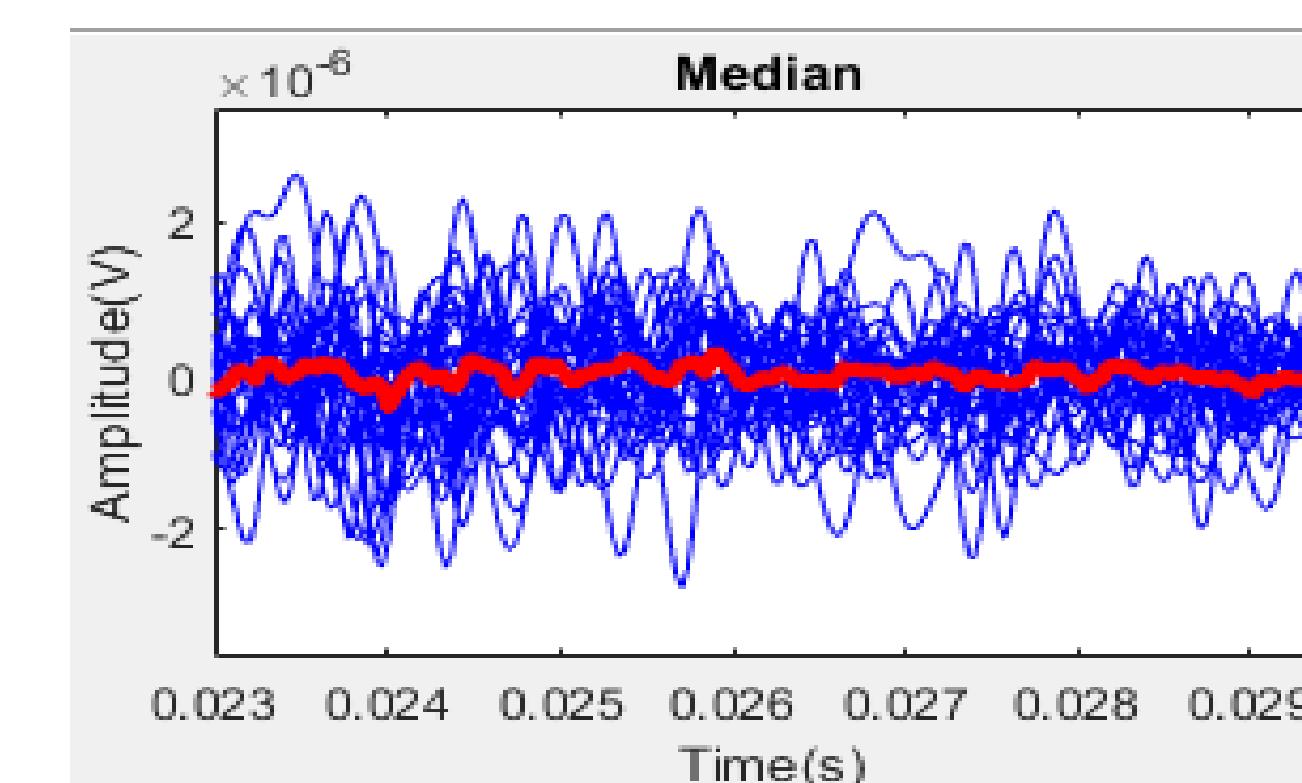


Figure 2: Median in the data

- Denoising is done to reduce distortions introduced by filtering.
- We get rid of common noise by calculating the median and subtracting it from each of the channels.
- $S_{Denoised} = S_{Noisy} - median(vS)$

4. Spike Alignment

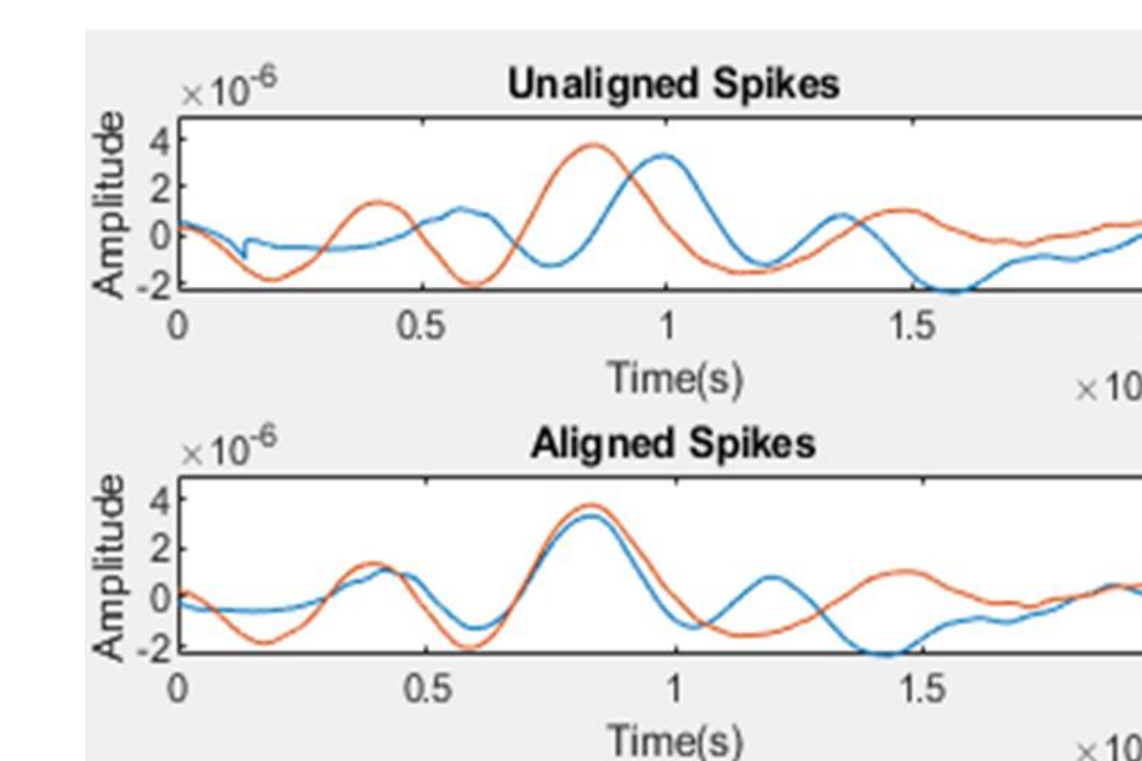


Figure 4: Aligning Spike in Time

- We aligned the spikes in time to better compare the similarities and differences between them.
- This makes feature extraction more accurate.

6. Clustering

- Spikes with similar features are likely to come from the same neuron, so we cluster neighboring points.

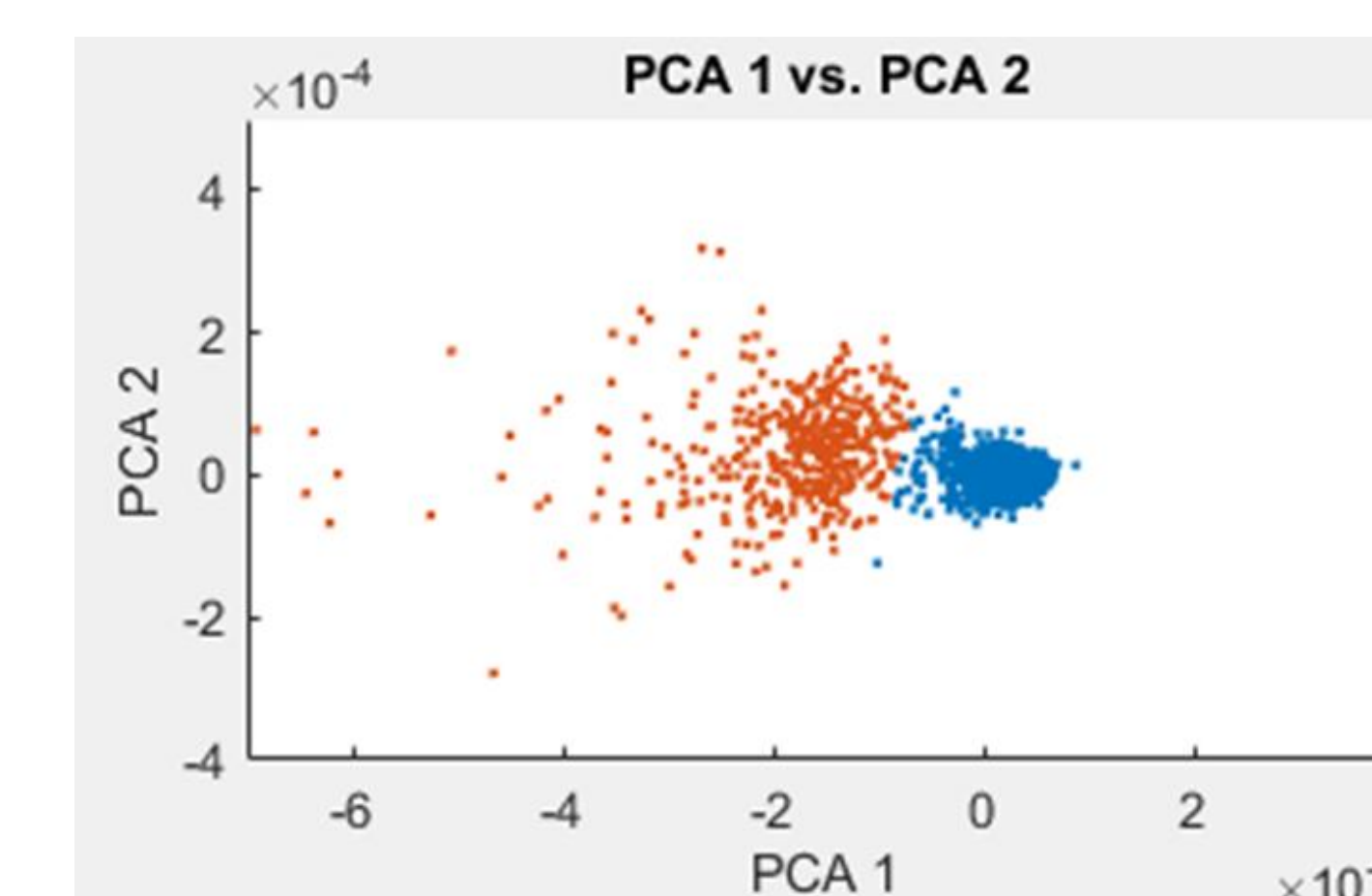


Figure 6: Clustered Spikes

Next steps

- Implementing Superparamagnetic clustering (SPC)
- Testing the algorithm against different data sets.

Acknowledgements

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References

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