Evaluation Performance of Spike Sorting Algorithms

Philip Vu
Biomedical Engineering
University of Michigan
Ann Arbor, United States

***Abstract*—Many questions in Neuroscience are dependent on analyzing neuronal spike activity recorded during certain behavior tasks. In other words, neural spike activity is the electrical activity that occurs in brain cells when active. For this reason data acquired from numerous neurons are essential in elucidating the underlying principle of neural information processing. Recently, commercially available electrode arrays have been developed to detect multiunit neural activity within the brain. However, development of efficient and reliable computational methods on classifying multiunit data lags behind the capabilities of current hardware. In practice, supervised spike sorting is tedious and time-consuming. Here, I compare and contrast two common spike sorting algorithms, list their positive and negative characteristics, and evaluate how well each method can reconstruct a spike waveform with a minimal amount of coefficients.**

I. FIGURES

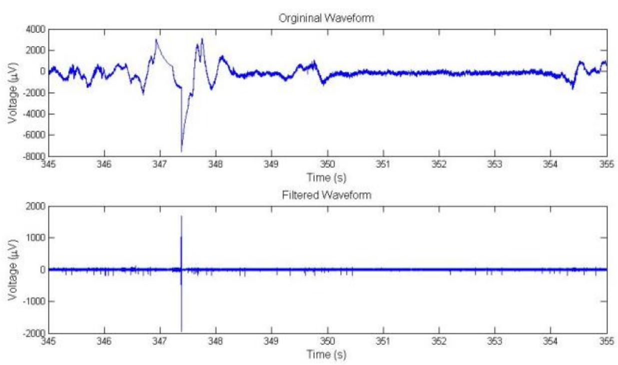

Figure 1: Top: A 10 second snippet of channel 1's original neural activity of an awake rat recorded for 10 minutes with a 16 channel carbon fiber microelectrode array in the rat's motor cortex. Bottom: 10 second snippet of channel 1's neural waveform after being passed through a 12^{th} order Butterworth band-pass filter with cutoff frequencies at 300Hz and 5000Hz.

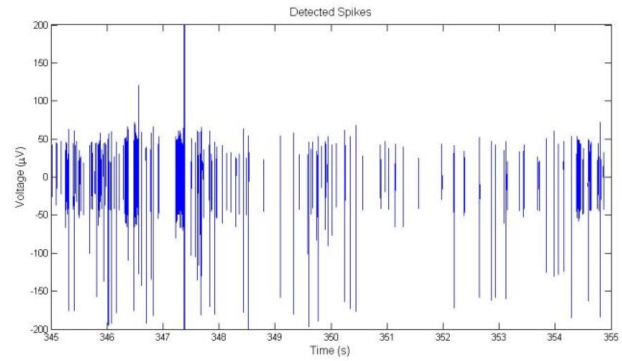

Figure 2: Individual 1 millisecond waveforms plotted after a detection spike algorithm was implemented.

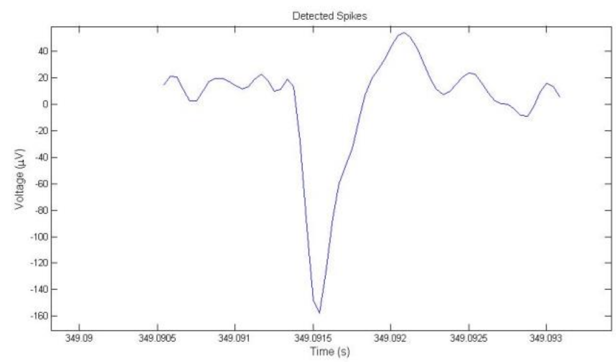

Figure 3: A 1 millisecond individual waveform taken from the detected spikes plot in Fig. 2. This waveform shows the characteristics of a single neural spike unit with a peak amplitude of -150 μV.

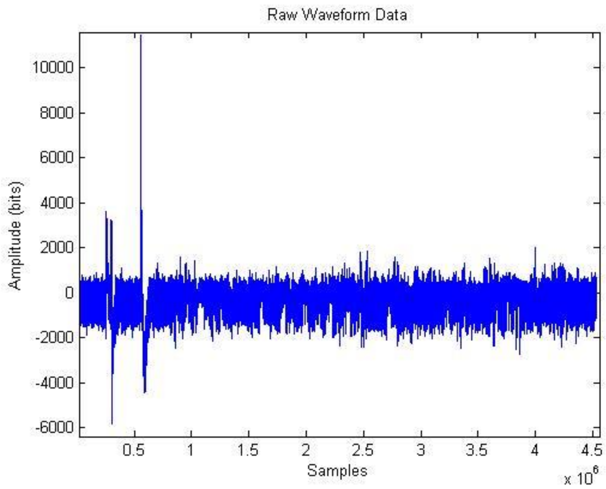

Figure 4: Raw neural activity recorded from the motor cortex of a rhesus macaque monkey during a grasping task.

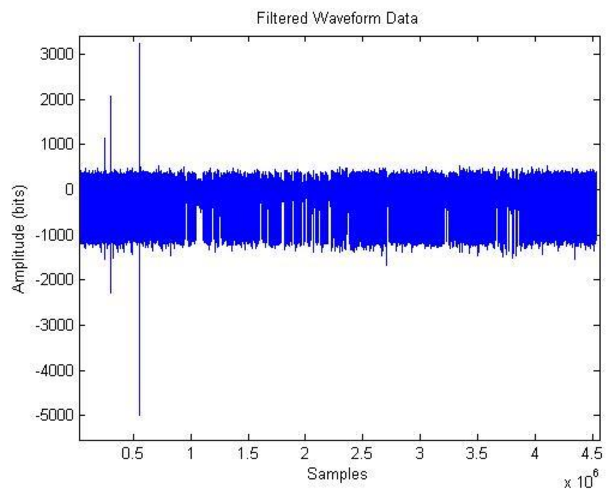

Figure 5: Raw neural data was filtered through a 12th order Butterworth band-pass filter with cut off frequencies at 300Hz and 5000Hz.

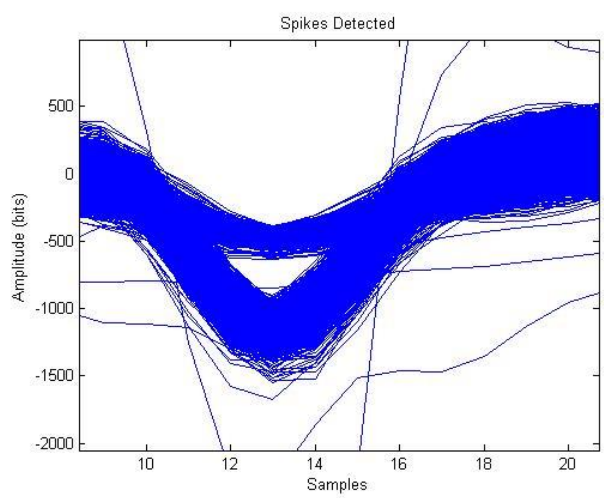

Figure 6: The spike detection algorithm captured multiple waveforms believed to be single unit spikes. Above is plotted "spike" waveforms overlapped on one another.

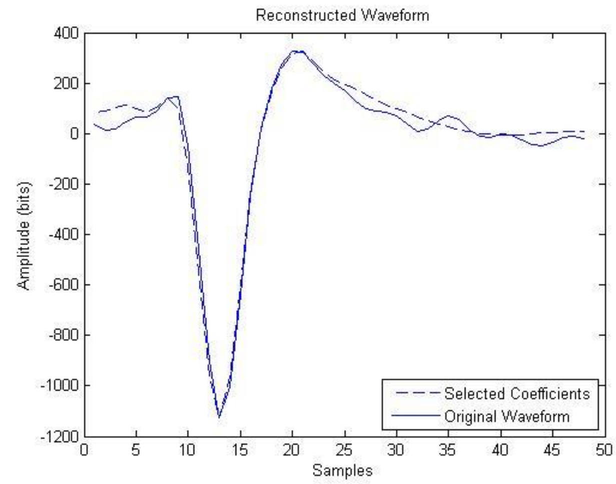

Figure 7: The detected spike data was then processed through principle component analysis for feature extraction. First four principle components were selected to reconstruct the original spike waveform.

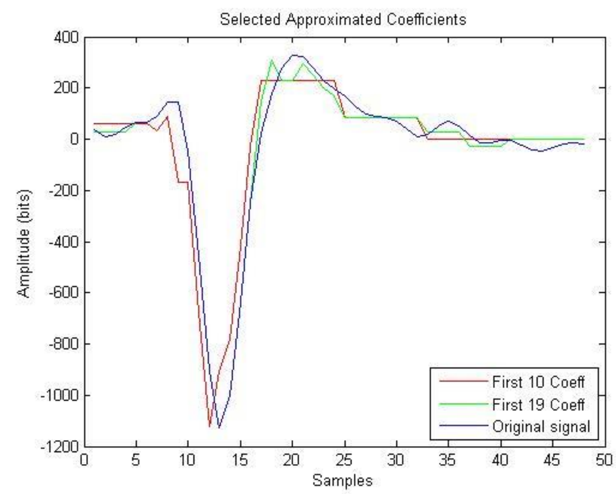

Figure 8: Detected spike data was also processed through wavelet transformation. The first 10 coefficients, determined from Lilliefors test, were used to reconstruct the original spike waveform (red). Then the first 19 coefficients were taken using the same test (green). Original signal is shown in blue.

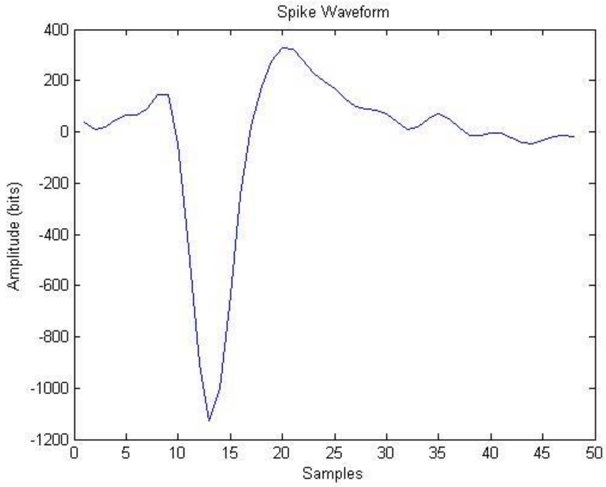

Figure 9: Single unit spike waveform taken from the detected spikes data set.

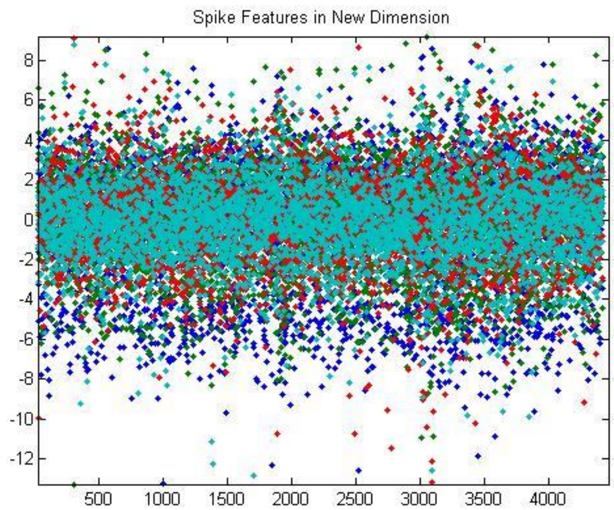

Figure 10: First 4 coefficient clusters plotted after applying principle component analysis. Blue designates the first principle component, green the second principle component, red the third principle component, and teal the 4th principle component.

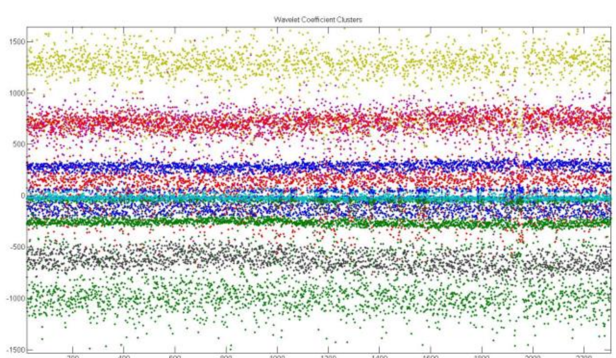

Figure 11: First 10 coefficient clusters plotted after applying wavelet transformation. The coefficients were chosen through applying Lilliefors test.

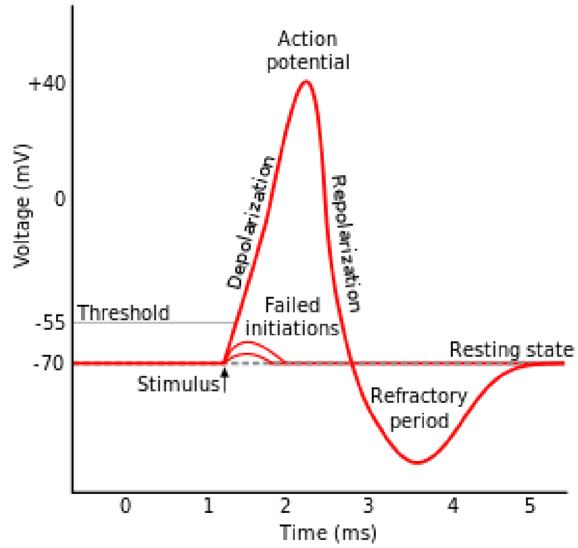

Figure 12: Characteristics of an action potential's rise and fall during an event.

A. Introduction

Many questions in neuroscience requires analyzing neural spike activity within the brain. A spike represents an action potential, which by definition is an event where the electrical membrane potential of a brain cell rapidly rises and falls. As seen in Figure 12, the rise is denoted as the depolarization of the membrane potential. Contrarily, the fall denotes the repolarization of the membrane potential until it reaches its resting state. Action potentials typically last for 1 millisecond. Multiple action potentials can be fired at once from a single brain cell. These firing patterns can be studied to understand brain functionality or be used in brain machine interfaces to control external prosthetics. However, in reality recording neural activity does not result in obtaining a perfect waveform as seen in Figure 12. Neural activity is jumbled with many artifacts and noise that makes extracting these spike waveforms difficult. Thus, signal processing methods are needed to obtain these spiked waveforms. A common protocol has been developed to produce various methods. The spike sorting protocol undergoes four stages: filtering, spike detection, feature extraction, and clustering. Here I perform three of the four procedures, evaluating two different methods for feature extraction. I list the pros and cons of each method and evaluate their ability to reconstruct a spike waveform using the minimal amount of coefficients from each method.

B. Method Description

The spike sorting methods were used on two different neural sets. The first neural set was recorded for 10 minutes from awake rats within the motor area of the rat's brain. The second neural data set was recorded for 10 minutes from rhesus macaque monkeys during a hand grasping task. A 96 channel Blackrock Utah array was implanted into the motor area (M1) of their brain. After loading the data into Matlab, I then used the signal processing toolbox incorporated within Matlab to further filter the data with a 12th order Butterworth band pass filter with cutoff frequencies at 300 and 5000 Hz. The 12th order band pass filter was chosen to have a -240 dB per decade roll off. This range is typical in cleaning up most of the noise seen in neural activity data. Based on hardware specifications of the Tucker Davis Technologies recording system, I sampled the signal at 24 kHz. The recording system consists of ZC16 head stage, RA16PA pre-amplifier, and RX6 Pentusa base station. The pre-amplifier has a high pass filtered at 2.2Hz, anti-aliased filtered at 7.5 kHz. After filtering the data, I manually snipped out any sections that blatantly looked like artifacts. From there I created a spike detection algorithm. The spike detection captured waveforms above a certain threshold as seen in Fig. 2. The threshold was calculated using the root mean square of the signal. Overall, the algorithm captures the indices whose data points are above threshold. Then, the maximum peak value of each waveform is determined. That maximum value acts as the pivot point to capture samples before and after the peak value. 1 millisecond of samples was captured for each peak found. Principle component analysis and wavelet transformation methods were utilized on the captured spiked waveform dataset. For principle component analysis, the first four principle components were used to reconstruct the original spikes waveform. Contrarily, for wavelet transformation the coefficients were selected through a Lilliefors test, which compares the cumulative distribution function of the signal with that of a Gaussian distribution with the same mean and variance. The deviation from normality was then quantified (Quian Quiroga et al., 2004). These selected coefficients were used to reconstruct the original spike waveform. The root squared mean error was then calculated to evaluate the performance of reconstruction with the minimal amount of coefficients.

C. DSP Tools

I've implemented two main in-class DSP tools, an IIR band pass filter and sampling techniques. The band pass filter had cutoff frequencies at 300 and 5000 Hz. In addition, I implemented two out-of-class DSP tools. First, I used principle component analysis (PCA), which is defined as an orthogonal linear transformation. The method measures the greatest variance by some projection of the data onto an arbitrary line. From there, the first coordinate with the greatest variance is defined as the first principle component and the second greatest is the second principle component. Mathematically the transformation has a row vector x(i) of X that projects onto a set of m-dimensional vectors v(k) = (v1,v2…,vm)(k) to form a new vector of principle component scores t(i) = (t1,t2,...,tp)(i). In other words, the data points are transformed to a new basis. PCA has a unique property of dimension reduction, which reduces the representation of the signal to a few vector components. Typically, the first two or three principle components contain more than 80% of the energy of the signal (Glaser and marks, 1968; Abeles, 1977). To date, this method is the most commonly used feature extraction technique for spike sorting. The second method, wavelet transformation, is a time-frequency representation of the signal. This transformation provides optimal resolution in both time and frequency domains and eliminates the requirements for signal stationarity (Quian Quiroga et al., 2004). Mathematically, it is defined as the convolution between the signal and the wavelet functions.

$W\psi\, X(a, b) = \langle x(t) \mid \psi a,b(t)\rangle$

where $\psi a,b(t)$ are dilated or contracted, and shifted version of a unique wavelet function ψ(t),

ψ*a*,*b*(*t*) = |a|^-1/2 ψ((t-b)/a)

where a and b are scale and translation parameters, respectively (Quiroga et al. 2014).

In spike sorting, determining what features best separate different shapes of spike waveforms is critical. Most recently, Quiroga et al. 2014 has demonstrated with simulated neural data that wavelet transformation performs better than PCA. Here I am interested in determining the minimum amount of coefficients needed to fully reconstruct a spike waveform. Using Matlab's wavelet toolbox I ran the wavelet coefficients selection 1-D reconstruction GUI. The GUI allowed me to manually select the coefficients that was selected through Lilliefors test. The way the wavelet decomposition algorithm works is a signal is filtered through a low-pass and high pass filter to split the signal into its high scale, low-frequency component and its low-scale, high frequency component. The two signals are then down sampled to maintain the original signals length. This down sampling still retains the important information to reverse the process and reconstruct the signal. Filter design is important in canceling out the effects of aliasing and determines whether perfect reconstruction is possible. Thus, the low- and high-pass decomposition filters are often closely related to their associated low- and high-pass reconstruction filters. With this algorithm, wavelet decomposition can occur at multiple levels. The Haar wavelet is the simplest wavelet and is used in the wavelet transformation of the neural data. Its mathematical representation is

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2, \\ -1 & 1/2 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

where ψ(t) is the wavelet function and Φ(t) is the scaling function. I chose this wavelet due to its orthogonal property to analyze local features of the input signals.

D. Results

After obtaining the detected spikes data, I took one captured spiked waveform as seen in Figure 9 and ran both PCA and wavelet transformation on the signal. For PCA the first four principle component scores were used. Figure 7 shows the original waveform and the reconstructed waveform. The root means squared error was calculated with a result of 39.45. Its normalized root mean squared is 2.71%. Figure 8 shows the reconstructed signals using the wavelet coefficients. The top 10 and the top 19 coefficients were chosen to reconstruct the waveform. Their root mean squared error were calculated to be 124.96 and 42.40 respectively. Their normalized root-mean-square are 8.6% and 2.92%. This demonstrates that principle component analysis stores most of the signal’s information within a few components. Whereas, wavelet transformation spreads the signal’s information in its coefficients to reconstruct the signal. Thus, more coefficients are needed to reconstruct the spike waveform as well as PCA. In addition, Figure 10 and Figure 11 shows the plotted coefficients for PCA and wavelet transformation respectively. In Figure 11 the top 10 coefficients of the wavelet transformation are plotted. The plot demonstrates that wavelet coefficients have distinct separation from one another, which benefits in classifying certain features of the signal, whereas Figure 10 shows that PCA coefficients overlap one another which may not be beneficial in feature extraction and wave separation.

E. Discussion

In spike sorting, feature extraction is an important step in identifying and separating spike waveforms that originate from different brain cells. It has been proposed that wavelets provide a good method for feature extraction due to its optimal resolution in time and frequency domains (Letelier and Weber, 2000; Hulata et al., 2002). The advantage of this is that wavelets discern localized shape differences since wavelet coefficients are localized in time. Contrarily, PCA retains most of the signal’s information within the first three principle components. Overall, this is not optimal for cluster identification as seen in Figure 10. Thus, wavelet transformation may be a better candidate in feature extraction and waveform separation when implementing spike sorting methods.

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