Fundamentals of Neuroengineering
Exercise 3 - ENG Signal Processing

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Introduction

The goal of this exercise is to understand how to process electroneurographic (ENG) afferents signals, using single-channel cuff electrodes, compare three type of signals as well as cuff and TIME electrodes. In the first part, three ENG cumulative signals are being preprocessed, classified and compared in terms of classification accuracy. The signals are a results of mechanical stimulation by means of pressure applied by VF filaments (*Touch Signal*), complete passive flexion (*Foot Flexion Signal*) and light touch executed by a brush (*Brush Signal*).

Exercice 1 - Processing of Cuff ENG cumulative signal

a) Understanding the signal to process

The signals of interest are located at were the labels are equal to +1, we can detect them visualy because they reach a high value when the stimulation are triggered. As seen from the Power Spectral Density (PSD) function of the signal in Figure 1, the signal of interest is located below 2kHz to 3kHz. Moreover, there is a distinguishable spike in the function around 70Hz, which we can safely say is due to electromagnetic noise. This means we can band-pass filter away the signal beyond these two frequency values and keep what is in between in order to focus on the signal of interest. Furthermore, we note that there might be other noise sources, as cross-talk disturbances coming from other signals or especially as disturbances due to motion artifact. Note that for the following sections, we plotted the graphs only for the Brush signal for space minimization purposes in order to respect the 10 pages report constraint, but the results are pretty similar for Foot Flexion and Touch signals.

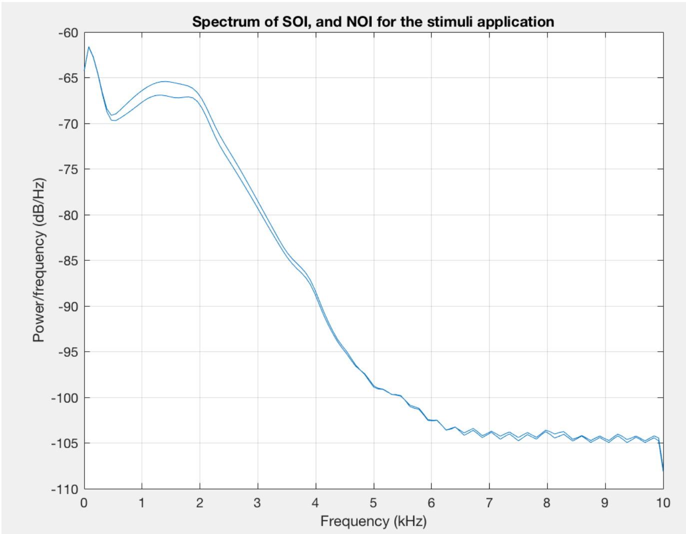


Fig. 1: Power Spectral Desnity of the raw signal recorded (Corresponding to real TIME recording) for the Brush signal.

b) Filtering

As mentioned in the previous section, low-pass filtering of the signal beyond 70Hz and 2kHz to 3kHz would be possible. However, in order to be consistent with the methods proposed in Raspopovic *et al.*, 2010, we chose the following cutoff frequencies for filtering: 800Hz and 2.2kHz, which are fairly close to what we mentioned. Figure 2 allows to observe the PSD function of the signal after filtering, which indeed shows that the signal of interest is now dominant.

c) Feature extraction

This section focuses on the computation and qualitative assessment of 3 types of features that can possibly be used for classification: Mean Average Value (MAV), Zero-crossing of the signal, as well as Wavelength (WL). Using a Running Observation Window (ROW) of 100ms, we plotted the graphs of these features, along with the representation of the corresponding labels, which will be used to determine the quality of each feature for classification. Those are represented in Figure 3. We immediately see that the Zero-crossing feature shows very poor results, as it does not seem to follow the signal corresponding to the labels, which means it cannot be used as a feature for classification. However, as seen in Figure 4, which is basically the same as Figure 3 but without the Zero-crossing feature, both MAV and WL seem to have good correlation with the labels. This means that those two may eventually be used for classification. Therefore, we chose to keep only these two from this point on and deeper assessment of their respective quality will be performed in the following sections.

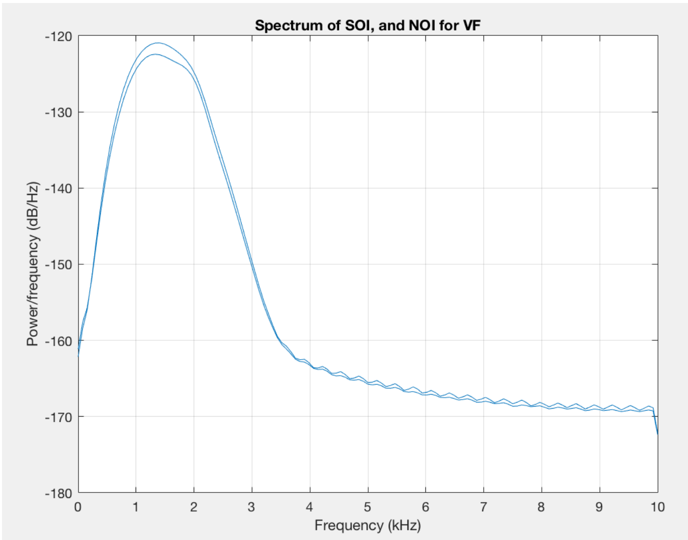
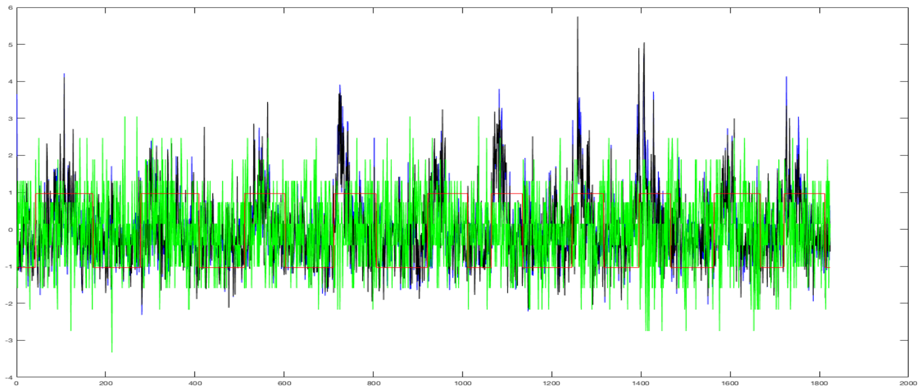
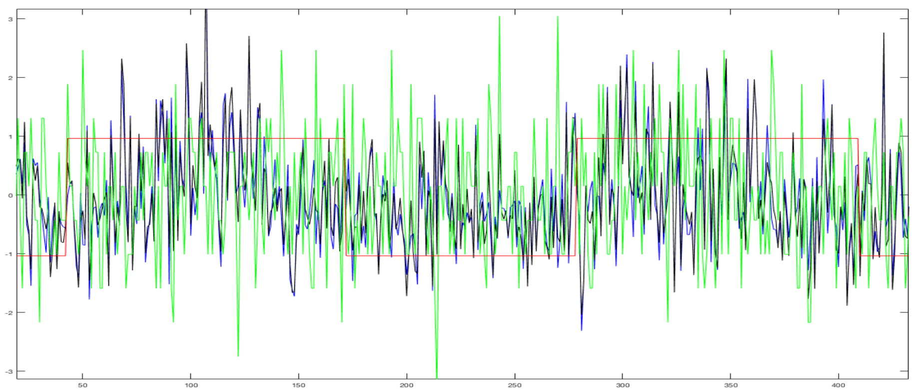


Fig. 2: Power Spectral Desnity of the signal recorded (corresponding to real TIME recording) for the Brush signal, after having applied a band-pass filter between 800Hz and 2.2kHz to keep the signal of interest only.

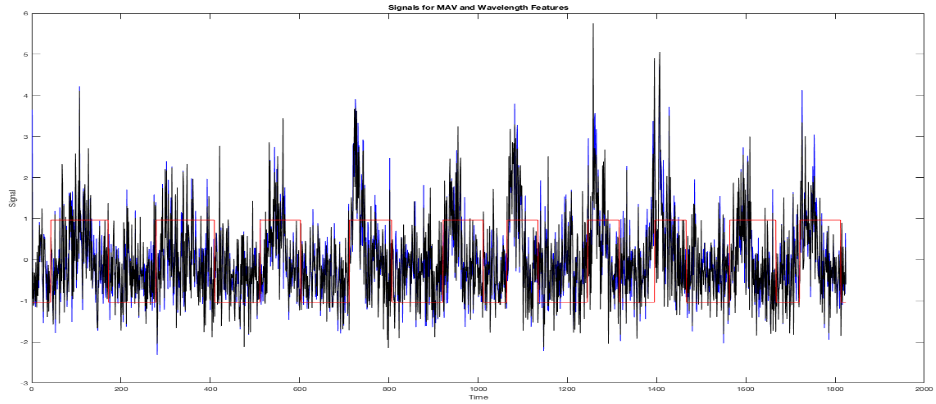


(a)

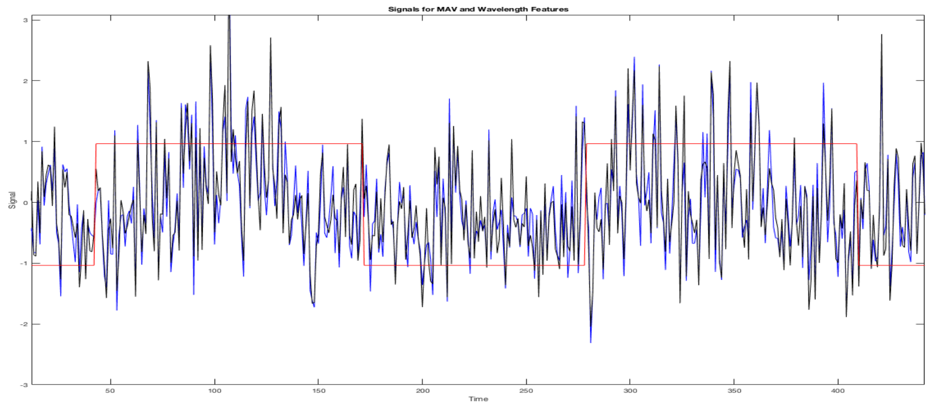


(b)

Fig. 3: Zscore plots of all 3 features (Green: Zero-crossing, Blue: MAV, Black: WL) and the labels (Red) for the Brush signal. a) Full overview of the signals. b) Zoomed version over the first 2 periods for better visualization.



(a)



(b)

Fig. 4: Zscore plots of only 2 features. Blue: MAV, Black: WL and the labels (Red) for the Brush signal. a) Full overview of the signals. b) Zoomed version over the first 2 periods for better visualization.

d) SNR calculation

In this section we compute the Signal-to-Noise-Ratio (SNR) of the features we chose to keep for the following - MAV and WL. This computation is done according to Raspopovic *et al.*, 2010 again, which give the following formula for this:
$SNR = 20 \times \log_{10} \frac{average(Feature_{stimulus})}{average(Feature_{rest})}$.

Table 1 shows the SNR values for both features and for each of the three types of stimuli. Firstly, the results are in the ball park of those presented by Raspopovic *et al.*, 2010 and, as we can see, for each signal the MAV feature seems to be of slightly higher quality than WL, as it carries a higher SNR, although both are pretty close. They are particularly high for the Foot Flexion signal. That being said, we would tend to prefer to use the MAV feature for classification later on.

SNR (dB)	Brush Signal	Foot Flexion Signal	Touch Signal
Mean Absolute Value	1.1804	2.4618	1.6346
Wavelength	1.1479	2.2595	1.6035

Tab. 1: Signal-to-Noise Ratio for MAV and WL computed for each of the 3 afferent single-channel cuff electrodes signals.

e)

As it is stated in the exercise, the results are different throughout the three signals. We would expect the Foot Flexion signal to be the easiest to recognize with a classifier. Firstly, its MAV and WL SNRs are the highest among the three signals, and the amplitude of the movement is higher than the two other signals, which in turn yields a larger amplitude difference between stimulus and rest states.

f)

There are at least two methods which could improve the SNR estimation for these signals. Firstly, the trigger is actuated by the person performing the experiment, which inevitably may cause a delay with respect to the real stimulus. Therefore, using an automatic cyclic triggering at the stimulus level might help in avoiding this delay. Moreover, the SNR is proportional to the diameter of fibers conducting the various stimuli. Therefore, using larger fibers may also improve the SNR estimation.

Exercice 2 - Processing of spike-like ENG from TIME and regenerative electrode

In this part, the data was recorded from an intraneural electrode. The stimuly corresponds to the foot flexion. On figure 5, the Neural signal (Corresponding to real TIME recording) is ploted to understand the signal to process. For this exercice, a matlab function was provided to computes the steps necessary to detect and cluster the spikes present in the recording. The parameters for the spike detection are the detection treshold, the sampling frequency and the length of the running window. First, we will define the right threshold to detect the spikes, then we will identify two types of spikes and lastly we will calculate the firing rate.

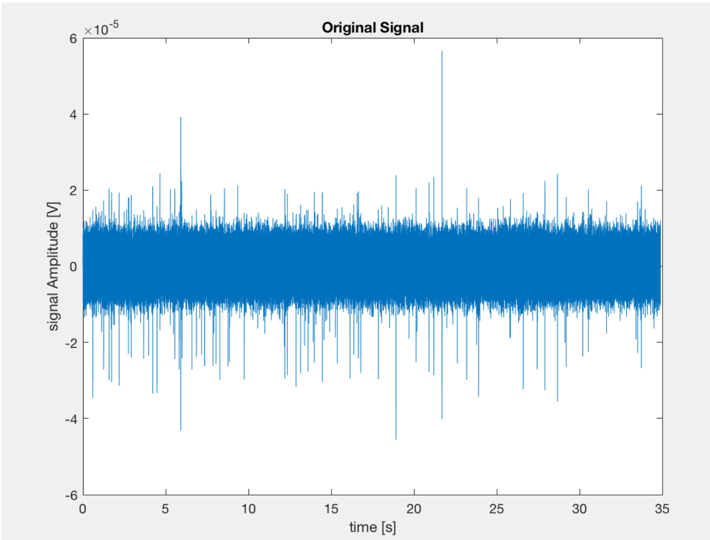


Fig. 5: Neural signal (Corresponding to real TIME recording) with respect to time

1) Vary the value of the Threshold

For a 2ms time window, we plot the first waveforms detected for every threshold in figure 6. We already see that with a threshold of 2 or 3 times the standard deviation of the signal, artifacts are detected as spikes. The first spike detected for a threshold of 4, 5 or 6 SD is exactly the same, so they overlap on the plot and only the curve of the threshold of 6 is visible. In table 2, we compare the different thresholds by looking at the computational time needed to extract the spikes and the number of spikes detected. It appears that a threshold of 4 SD already differentiates the noise from the spikes with a reasonably low complexity. We will thus use this threshold for the remaining of the exercise.

Threshold [n*SD]	computational time [s]	Number of spikes deteted
2	0.69	6240
3	0.07	719
4	0.04	100
5	0.05	69
6	0.06	56

Tab. 2: Spike detection results for different detection thresholds

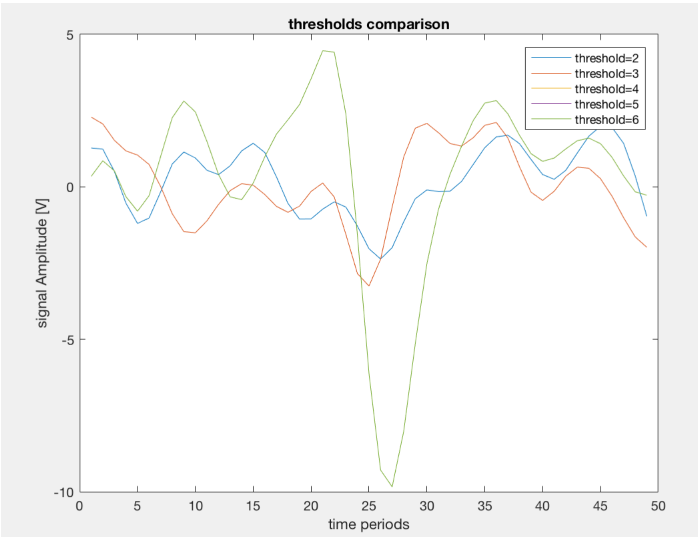


Fig. 6: Plot of the first spikes detected for different threshold values

2) PCA analysis

Using the optimal threshold of 4 SD, 100 spikes are extracted with each 49 features which correspond to number of samples in a time window of 2ms. After applying the PCA to the extracted spikes, the 2 first principal components were extracted and stored to be analyzed. These 2 first principal components correspond to the 2 samples per time window which describe the variance of the signal the most.

3) Spike Sorting algorithm

The 2 Principal components can be clustered into 2 groups using Kmeans. Two clusters appear because two types of spikes can in fact be differentiated (see figure 7). Proprioceptive signals, which is the type of signal generated with foot flexion are induced in different axons of the nerve in which the electrode is inserted. With a Cuff electrod, only the overall nerve activity can be detected but with a Transveral Intrafascicular Multichannel Electrode (TIME), the selectivity is increased and allow to differentiate the contribution of single axons. So the two types of spikes observed are in fact signals going through different axons and depending on their size and property, the signals are different even if generated by the same external stimulus.

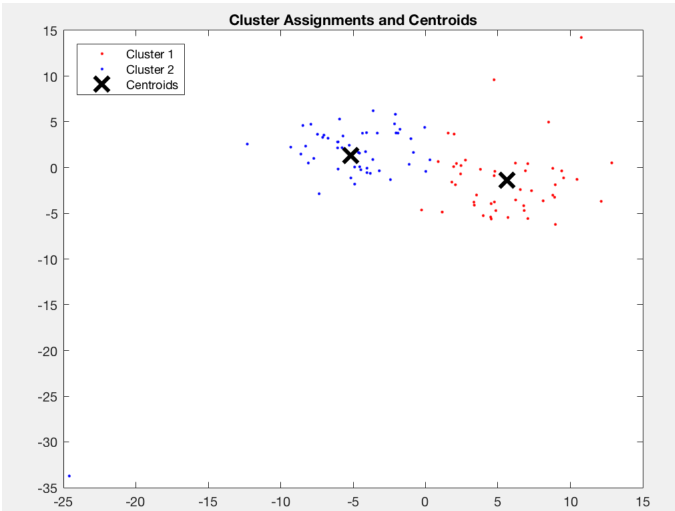


Fig. 7: Plot of the two clusters of data and the centroids of each cluster with Kmeans

In figure 8, we ploted 3 spikes belonging to cluster 1 and 3 spikes belonging to cluster 2. By visualizing them, the difference becomes very clear. The first type of spikes can be characterized by a large bump of about -4 while the second type of spikes can be characterized with an first bump of 4 follow by a narrow bump of -8.

4) Firing rate

The firing rate represents the activity over time of the recorded fibers. The firing rate calculated after extracting spikes, using a moving window of 200ms, is 1.7767 [n spikes/seconds]. In figure 9, we plot on the left the spike appearances with the original signal. We see that the location of the detected spikes is in fact very precisely correlated with the spikes that we can visually observe. After generating spikes according to the firing rate, we plot them on the right figure with the original signal.

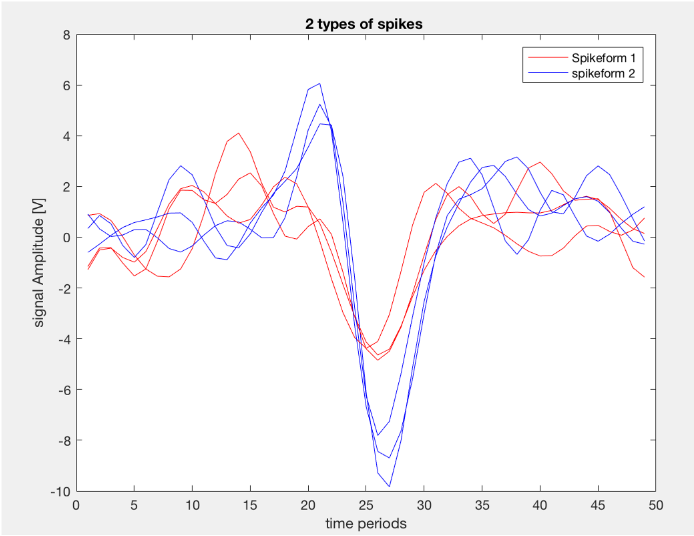
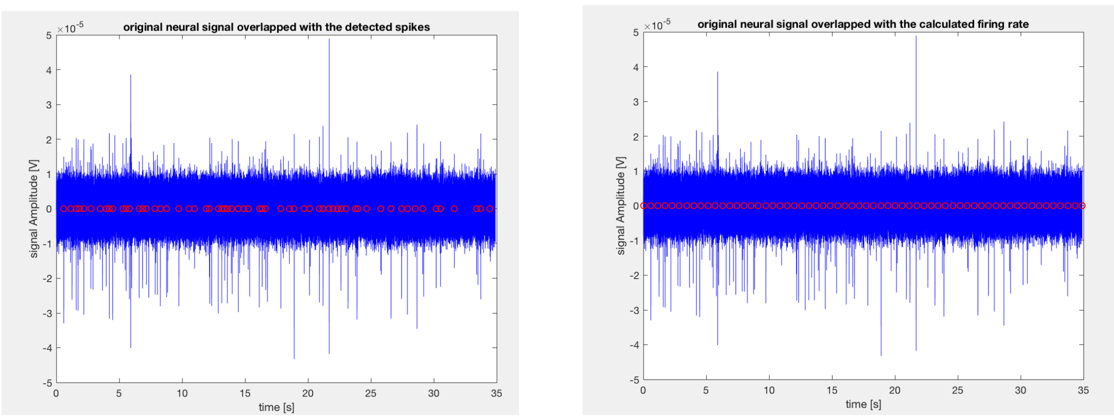


Fig. 8: Plot of the spikes waveforms contained in the two clusters in two distinct colours



(a) Plot of the original neural signal overlapped with the detected spikes

(b) Plot of the original neural signal overlapped with the calculated firing rate

Fig. 9: orginial spikes and predicted spikes with the firing rate