Holland Ernst
21 February 2023

HW 1 – PNS

Pre-processing

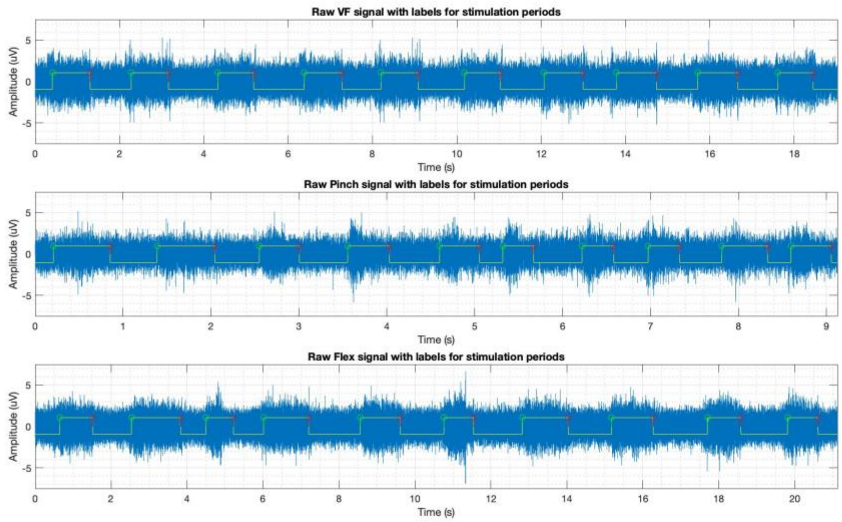


Figure 1. Raw signals with labels of stimuli location. 1.1 Raw VF signal for vertical comparison. 1.2 Raw Pinch signal for vertical comparison. 1.3 Raw Flex signal for vertical comparison. *Note: Green stems indicate the trigger of the stimulus, red stems indicate the fall of the stimulus, yellow lines track stimulus and rest period. Z-score for each signal was performed to normalize scaling for comparison.*

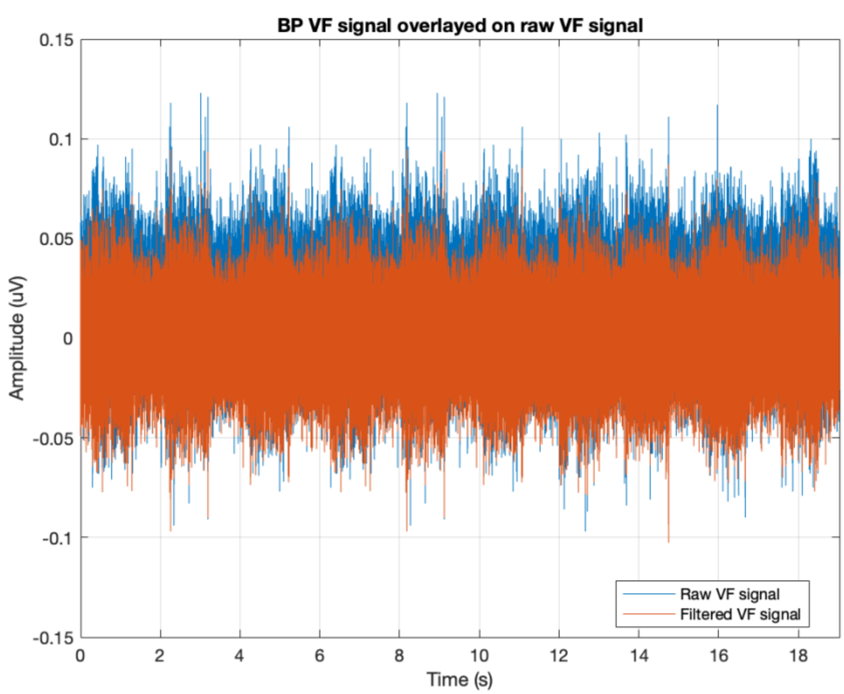


Figure 2. Bandpass filtered VF signal overlayed on raw VF signal. The filtered VF signal*Note: Z-score for each signal was not necessary because the primary interest is comparing the signal to itself, rather than normalizing across multiple stimuli for comparison.*

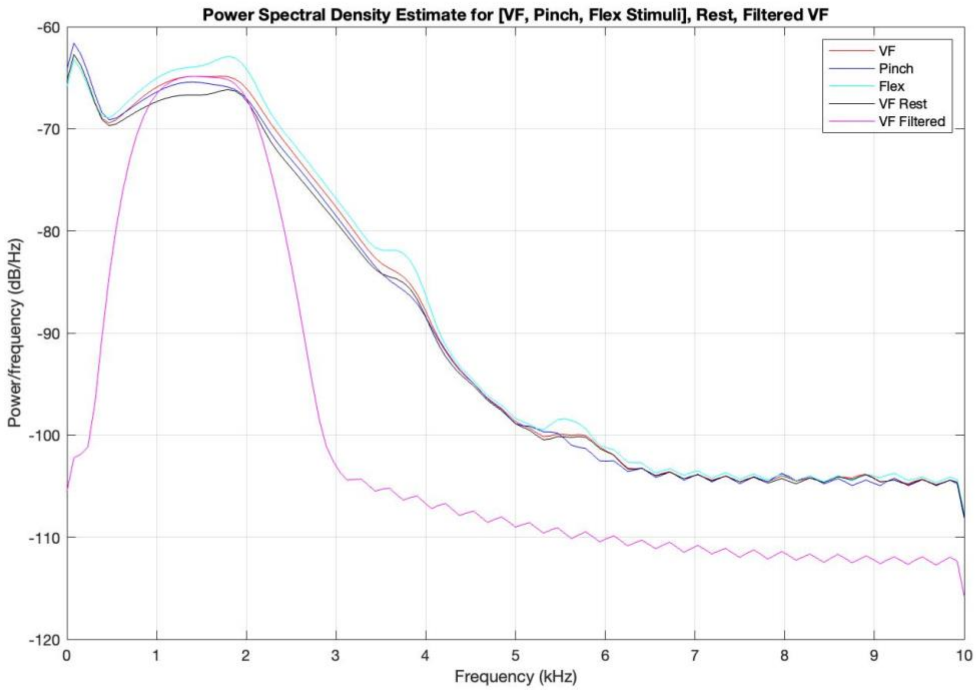


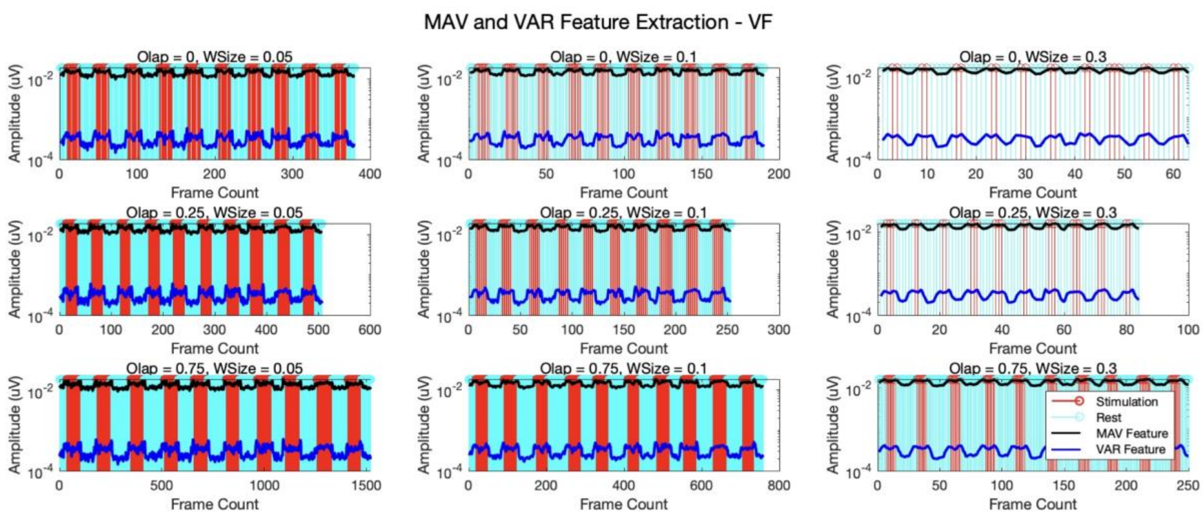
Figure 3. PSD Estimate for Stimuli, Rest, and Filtered VF Stimulus. The pre-filtered PSD estimates for each stimulus (VF – red, Pinch – blue, Flex – cyan) are plotted. Figure uses VF Rest for PSD estimate (plotted in black) of rest because there was no significant visual difference among the rest for each stimulus. A comparison between VF raw PSD estimate and VF Filtered PSD estimate is shown in pink and red. The VF signal was filtered using a zero-phase filter and a fourth order Butterworth bandpass filter implemented from 800Hz-2200Hz [1]. *Note: There should be no difference between rest during each stimulus – biosignals create inherent differences in practice.*

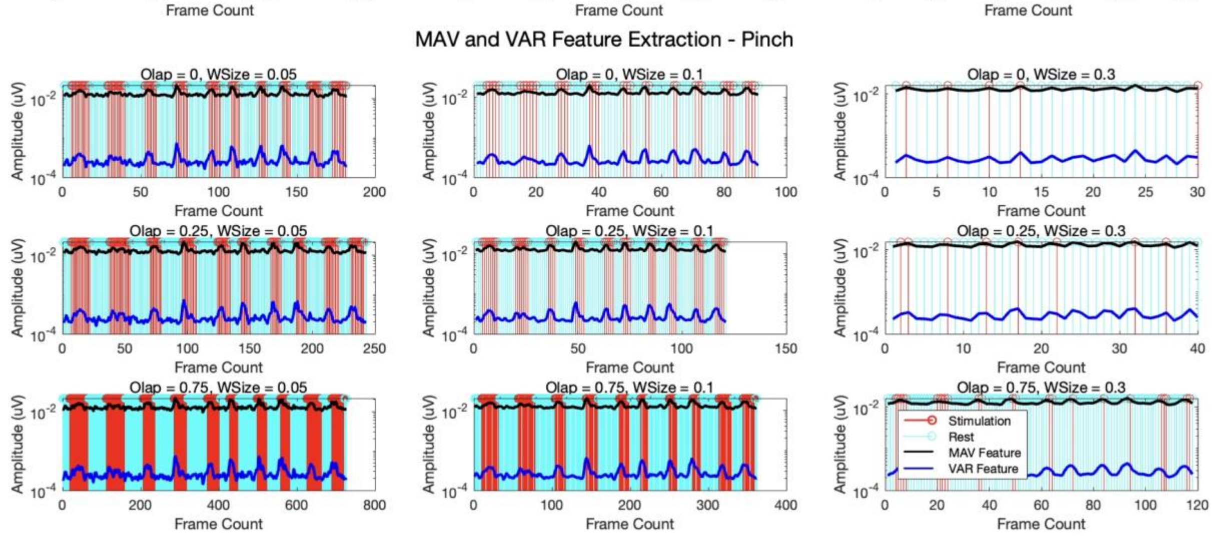
a) According to the Power Spectral Density Estimate in Figure 3 the most relevant frequency range for discrimination between the different stimuli and rest periods appears between approximately 500-3000Hz. While having similar shape, there is a noticeable power difference in the plot for each stimulus and rest period across this range of frequency bands. Within 500-3000Hz, there is a peak frequency for each stimulus between 1000-2000Hz that indicates neural activity associated with the respective stimuli. The peak at ~1500Hz and consistent power decline until ~4000Hz, where the signal power begins leveling off, suggest that the frequencies after ~3000Hz contribute less power to the signal. Additionally, the gap between VF, Pinch, Flex, and Rest around 1000-2000Hz indicates discriminatory power in this frequency range. Particularly, the gap between Flex and the other signals suggests its large discriminative power in relation to the rest of the classes.

b) Filtering is useful because it reduces unwanted noise present in the signals, allowing more accurate spectral characteristics in the signal as a result of improved SNR. Specifically, the use of a bandpass filter will likely decreases variance from the original signal. Not only does this improve the clarity of the PSD plot, but it also allows for the isolation of frequency components. This improves the ability to identify how different frequency components contribute to the overall profile of the signal.

c) Figure 2 shows the differences between the VF raw signal and the VF filtered signal. The discrepancies between the overlayed signals are minute, though visually noticeable. As the selected range for the bandpass filter was cutoff below 800Hz and cutoff above 2200Hz, the figure suggests the efficacy of the bandpass filter at increasing signal-to-noise ratio (SNR) and focusing frequency content to the selected range. This is evident in the PSD plot overlay in Figure 3. VF Filtered exhibits a narrow range of frequencies, particularly retaining signal power between 800- 2200Hz. Though, the filter did not perfectly filter the raw VF signal, as shown in the remaining power of undesired frequencies.

Feature Extraction





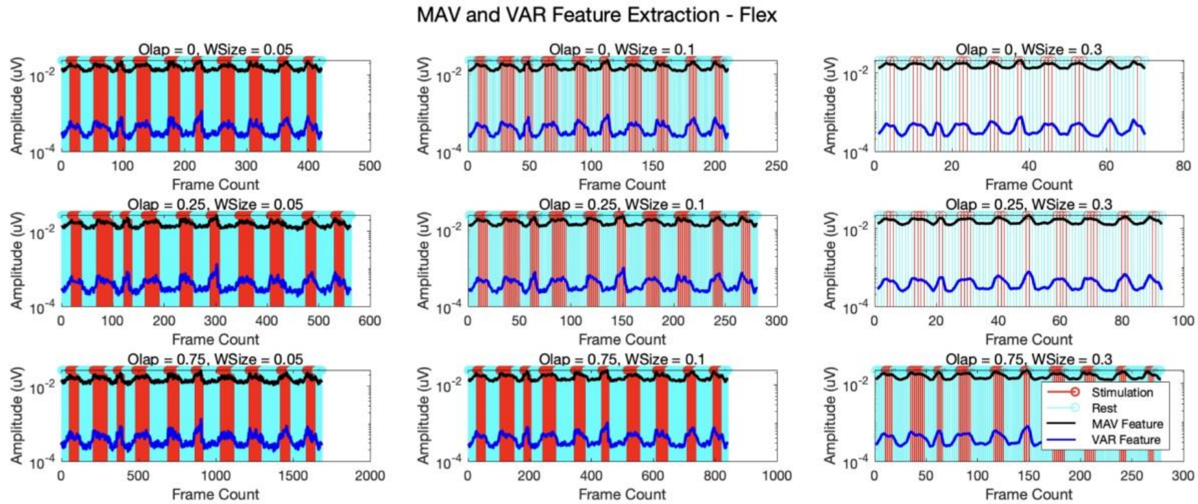


Figure 4. MAV and VAR Feature Extraction for Each Stimulus with Labels of Stimulation Intervals. Each figure contains nine plots representing the combinations of overlap (0, 0.25, 0.75) and window size (0.05, 0.1, 0.3) for each feature. The plots retain the inherent amplitude of each feature by setting the y-axis to a log scale, which allows visualization of both features. *4.1. VF signal. 4.2. Pinch signal. 4.3. Flex signal.*

a) By visual inspection of the plots, the best values for WSize and Olap are 0.1 seconds and 25%, respectively. Referencing Figure 4.1-4.3, the number of features visibly decreases from left to right for a given overlap as the window size increases from 0.05s to 0.3s. A greater number of features better captures the signal, though, an excessive number of features results from an insufficient window size and thus leads to increased variance. On the other hand, the number of features visibly increases from top to bottom for a given window size as the overlap increases from 0% to 75%. Naturally, the best result has a balance of both window size and overlap. The choice of 25% overlap rather than 0% overlap or 75% overlap stems from this balance, as well as the consideration of frame count. A larger frame count provides more flexibility in choosing smaller window sizes without sacrificing the overall coverage of the signal. However, it can be too big and cause increased variance in the signal due to high granularity. Ultimately, the consideration of window size, overlap, and frame count helps balance the need for temporal resolution and feature granularity.
b) Cross-validation is one better approach for optimization of the hyperparameters, WSize and Olap. Random search is a stochastic technique that could be employed to randomly search the data space and estimate the hyperparameters. Though capable of failing to identify the true optimal combination of hyperparameters due to random sampling, random search is computationally inexpensive and a robust technique. On the other hand, grid search has a higher likelihood of overfitting the hyperparameters on training data and tends to be computationally expensive. However, grid search is also extremely thorough, as it evaluates all combinations.
c) The visuals in Figure 4 display the ability of MAV and VAR features for discriminating between Rest and each of the stimuli. To generalize this ability, the more solid red and cyan lines indicate a greater discrimination between rest and stimulus. This is particularly apparent in the Flex features in figure 4.3, as only Olap = 0 / WSize = 0.3 and Olap = 0.25 / WSize = 0.3 have intermittent red and cyan stems, while the rest of the plots

clearly discriminate between rest and stimulus. VF features in Figure 4.1 appear to have similar discriminatory power between rest and stimulus periods as in Figure 4.3, which varies from the large difference in discriminative power between the two classes in Figure 3. In Figure 4.2, on the other hand, more than 50% of the plots prove difficult in visually discriminating between rest and stimulus periods for the Pinch stimulus. Regarding discrimination power using MAV or VAR, there does not appear to be a difference between the capabilities of each feature.

Feature Selection

	MAV	VAR
VF	1.457	2.690
PINCH	1.240	2.756
FLEX	2.226	4.564

Table 1. Feature SNR for Stimulus to Rest. To estimate the discriminant power of extracted MAV and VAR features, the SNR metric was computed in dB for stimuli with respect to rest.

a) The VAR feature yields better SNR than the MAV feature, as shown in Table 1. Naturally, the VAR and MAV features are independent, meaning that VAR and MAV features encode different information about the signal. As a result, the classifier will likely detect classes better using the combination of the two features. Hence, the VAR feature is more suitable for the classification of the signal labels. Similar for both the MAV and VAR features, the Flex class holds the highest SNR values among the three stimulus types, which suggests that the Flex class would be the easiest to detect using the classifier. The higher SNR, and likely the classification performance, observed in the proprioceptive Flex stimulus can be attributed to the diameter of the larger proprioceptive fibers responsible for encoding pertinent information regarding the signal response [1].

Classification

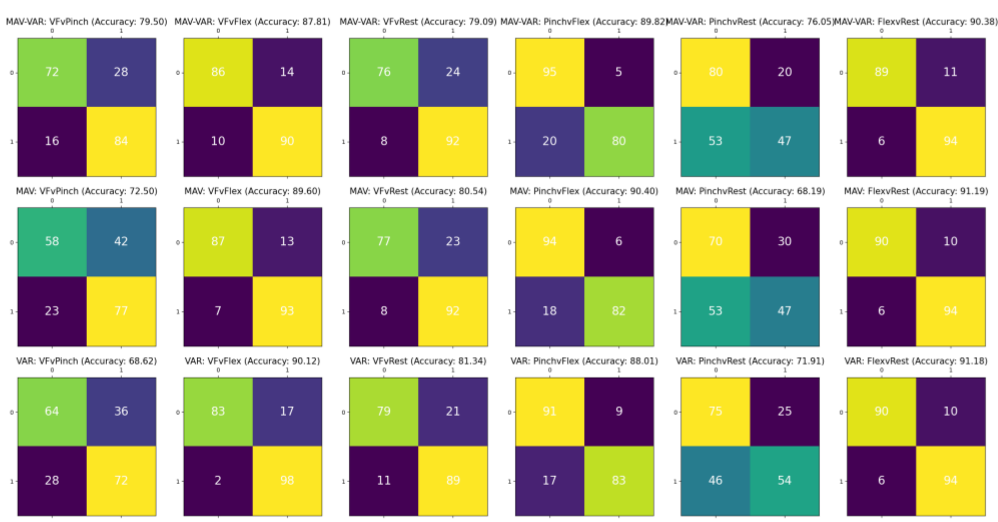


Figure 5. Confusion Matrices depicting the classification accuracy across a 10-fold cross validation model. Rows and columns labeled as (0,0) represent True Negative, labeled as (0,1) represent False Positive, labeled as (1,0) represent False Negative, labeled as (1,1) represent True Positive.

a) Figure 5 depicts classification accuracies using MAV, VAR, and a combination of the two features. The model detects the VF versus Rest with accuracies greater than 79% and with 81.34% from the VAR feature, the Pinch versus Rest with accuracies greater than 68% and with 76.05% from the MAVVAR feature, and the Flex versus Rest with accuracies greater than 90% and with 91.19% from the MAV feature. The model detects the VF versus Pinch with accuracies greater than 68% and with 79.50% from the MAVVAR feature, VF versus Flex with accuracies greater than 87.81% and with 90.12% from the VAR feature, and Pinch versus Flex with accuracies greater than 88.01% and with 90.40% from the MAV feature. The bias does not vary heavily across features for a given classification, however, the bias becomes unpredictable across classifications. Especially in the case of the Pinch class, there tends to be greater error in addition to the exacerbated bias. On the other hand, the Flex class consistently observes limited error and limited bias. The VF class falls between the other two classes. The confusion matrices prove that the Flex class has the greatest discriminative power, enhancing the classification rates from the model. This conclusion aligns with the predictions from Figure 3 and Table 1.

Feature	Average Accuracy (%)
MAV	82.02
VAR	81.86
MAVVAR	83.78

Table 2. Average Classification Accuracy per Feature. The accuracy values are computed by averaging the accuracy values of each classification for a given feature. *Note: the average accuracy values do not statistically represent performance of each feature but will be used as a holistic metric for overall comparison.*

b) Between the VAR and MAV features, it was anticipated that VAR would achieve higher accuracy due to its superior SNR values presented in Table 1 compared to MAV's SNR for each class. However, the average accuracy values in Table 2 reveal that MAV exhibits better overall performance. This discrepancy suggests that while VAR has a higher SNR, it may not effectively discriminate between classes as it might not capture the crucial features contributing to classification accuracy. This observation aligns with the understanding that variance ratios may not be as relevant to signal characteristics as mean ratios. Also, the SNR fails to consider noise features that could impact classification performance, indicating the potential robustness of the MAV feature.

c) Physiological signals are non-stationary, meaning that the k-fold validation would need to systematically and sequentially splits the data into train and test in order to retain temporal characteristics of the signal. Such a split would lead to a fair assessment of the classifier's generalization ability as a result. The k-fold cross-validation appropriately represents the classifier's ability to generalize the signals by partitioning the temporally relevant data into equally sized epochs, allowing the model to focus on spatial components of the signal.

References

[1] S. Raspopovic, J. Carpaneto, E. Udina, X. Navarro, and S. Micera, ”On the identification of sensory information from mixed nerves by using single-channel cu↵ electrodes,” Journal of NeuroEngineering and Rehabilitation, vol. 7, no. 1, p. 17, 2010/04/27 2010.