Evaluating Processing Differences Between Tactile and Electrically Stimulated Percepts

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Abstract

Advances in neural technology have enabled control of prosthetics using neural signals; however, users rely solely on visual feedback to confirm movement. It's been shown that sensory feedback is critical for precise motor control. By electrically stimulating the sensory cortex through direct electrical stimulation, we can provide sensory feedback to the user and create artificial percepts. New research has found that subjects have slower reaction times when experiencing artificial percepts versus tactile touch, suggesting that the processing of these two phenomena are different. Here, we take a closer look at electrocorticography (ECoG) signals recorded during natural haptic touch and various sensory stimulation conditions. After extracting features including frequency band powers and spike related activity, we train a random forest classifier that reaches 98.9% accuracy on classifying between various stimulation conditions. By looking at model weights, we observe what features are the most defining: the number of spikes in the signal and the distance between the spikes. Our results give a foundation to work towards understanding the mechanism of sensory stimulation for application in motor prosthetic use.

1 Introduction

Spinal cord injuries (SCI) frequently cause loss of motor or sensory function **[1]**. The spinal cord acts as a pathway from the brain to the rest of the body, so when there is partial or complete damage, the brain cannot effectively send signals to the body or receive sensory signals from the body. The brain remains fully intact though and can still process sensory inputs, which is why patients with SCIs can still talk, see, think, etc **[1]**. We can use brain-computer interfaces (BCI) to help restore the lost functions. In modern BCI research, we're able to decode a patient's neural activity and use it to control a prosthetic arm **[2]**. However, user's currently rely solely on visual feedback to confirm movement of the prosthetic. Research has found that sensory feedback is extremely important for precise motor control **[3]**, which motivates research to accomplish sensory feedback methods to improve prosthetics.

We can have BCIs provide sensory feedback through direct electrical stimulation (DES). To accomplish this, we would attach sensors to the prosthetic that detects where and when a touch is detected, and then we would stimulate the brain in the corresponding sensory region such that the user feels the touch, creating a closed loop system. This method works by sending a targeted electrical signal to elicit the perception of touch when stimulating over the primary somatosensory cortex corresponding to the specific body part where touch has occurred. The stimulation is typically done with biphasic, bipolar, charge-balanced square waves **[4]**. We can customize the signal by changing the current amplitude, pulse frequency, train duration, or pulse width. Several studies have looked into how changing each parameter changes the perception **[5]**. By optimizing these parameters, researchers can elicit precise sensations and improve the sensory feedback of motor prosthetics.

Prior research in the GRIDlab has found that subjects are able to perceive natural touches faster than the artificial ones **[6]**. In other words, subjects have slower reaction times when experiencing artificial percepts versus tactile touch. To learn more about the processing differences between them, here we examined ECoG signals from subjects during an experiment where they either received sensory percepts on their hand via DES or through natural touch and investigated whether there were processing differences to explain the difference in reaction time response.

2 Method

The dataset we use is from **[6]**. The subjects of the experiment are patients being treated for medically refractory epilepsy at Harborview Medical Center and have consented to participate in research. For this experiment, the researchers artificially stimulated the subjects through DES in the hand region of the somatosensory cortex, stimulated them naturally by touching their hand with a tactor, and recorded their reaction time to the stimulus by having them press a button when they felt something. They used 64 ECoG electrodes implanted invasively to record brain signals throughout the whole experiment. For our paper, we look at only one of these subjects.

Dataset epoching

The first step was to extract the various trials out of the dataset and epoch all of the data. As seen in **Fig 1**, the button press data for one subject is an 11.5 minute signal that spikes whenever the button is pressed down. However, since the sampling rate is very high, 24414 Hz, each button press spans thousands of points in the signal. A similar observation was made for the tactile signal which spikes whenever a natural touch stimulation occurs. To decode this information, we obtained the indices of the elements that are above a threshold value of 0.008. We then split the data into sections by separating indices that are over a second apart which indicates time between trials. The beginning index of each split is the index we used to represent the button press. We did the same for the natural touch to extract the initial touch onset. For the stimulation trials, the dataset already included the onset and offset times. However, to separate the stimulation trials into the various conditions, we looked at the pulse amplitude (PAmp) and the number of pulses (NPul) and split them up based on **Table 1**. Conditions 1-6 are the direct electrical stimulation conditions.

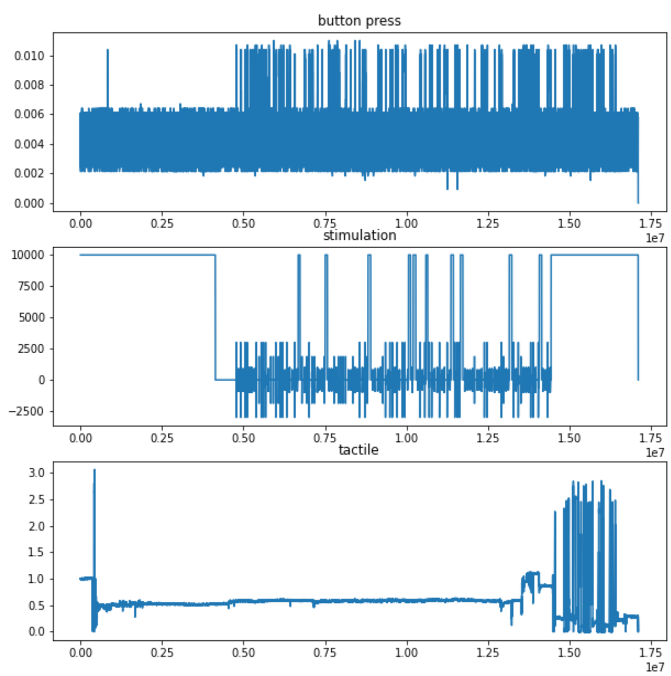

Figure 1: The top graph is the button press signal with each spike representing a button press. The middle is the stimulation signal with various amplitudes and spikes expressing different conditions. The bottom is the graph of the natural touch signal with each spike representing a touch. The X axis for all of the graphs is the samples and the Y axis is the amplitude of the signal.

-1	Natural touch	19
0	Null case	21
1	2 primed pulses - 3.75 mA	9
2	2 mA	19
3	1.6 mA	1
4	1.79 mA	7
5	1.6 mA + prime @ 6	20
6	2 mA + prime @ 6	20

Table 1: The 8 conditions for the subject. Condition -1 is the natural touch case, 0 is when there was no stimulation, and the remaining 6 are the various artificial stimulation cases. The priming pulses are initial pulses at the beginning of the stimulation. The rightmost column is the number of trials for each condition. The stimulation conditions were presented first in a random order, followed by the natural touch and null cases in a random order.

Once the stimulation onset indices were obtained, we checked the time between the onset indices and the nearest button press indices. If the nearest button press was before the offset, then we count that as a successful stimulus and include the trial in the rest of the analysis. **Fig 2** shows the various reaction times of each trial split by condition. As expected by previous research **[6]**, the natural touch case had the fastest reaction time. Using the onset and the beginning index and the button press and the end index, we split the ECoG signals and epoch the data by trial, keeping track of the reaction time and condition for each trial.

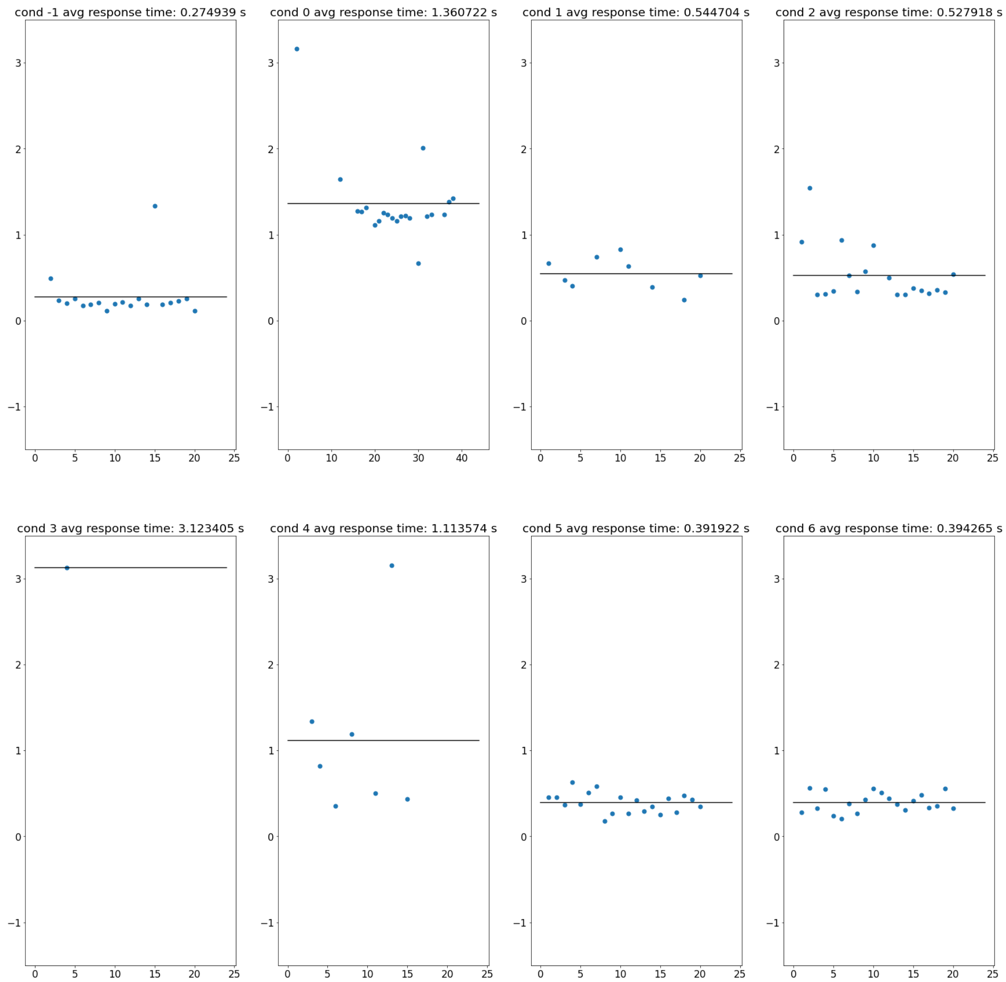

Figure 2: Reaction times of the various conditions for each trial. The horizontal bar across is the mean. The X axis is the trials and the Y axis is the reaction time in seconds.

ECoG Signal Processing

After epoching, we performed signal cleaning and filtering on the ECoG signals. In **Fig 3,** it's very noticeable that the raw signal has residual stimulation artifacts that need to be removed in order to examine the underlying neurophysiology. To remove the stimulation artifacts, we developed an algorithm that detects peaks and valleys that are over one standard deviation out of the mean and smooths them out by averaging the values around them to reveal the true signal underneath.

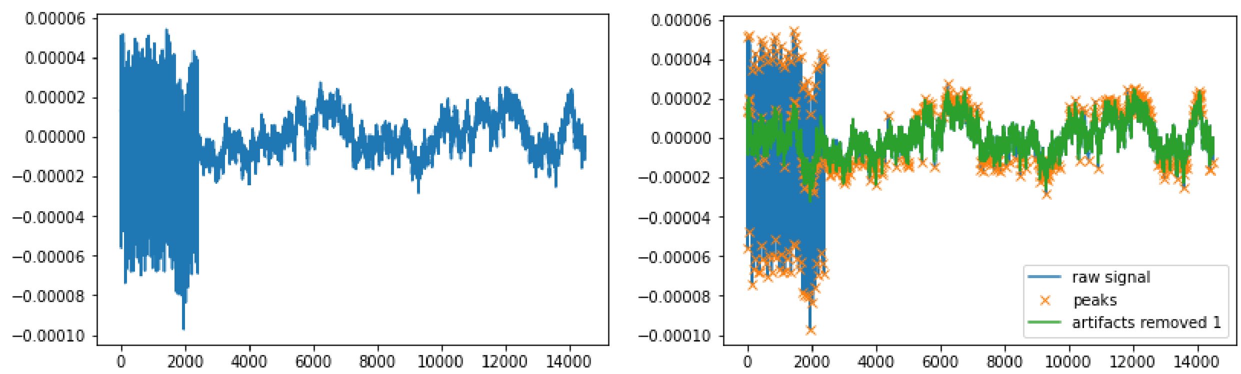

Figure 3: On the left is the raw EEG signal from one of the epoched trials. On the right is the same signal with the artifact removal algorithm which highlights the detected peaks and the new smoothed signal.

Once the artifacts were removed, we ran the signal through a second order butterworth bandpass filter to extract just the neural signals (0.1 to 200 Hz) and a notch filter at 60 Hz to remove line noise. Once the signal is fully filtered, we extracted the power at common neural frequency bands (**Fig 4**). We ran the fully filtered signal through additional second order butterworth filters at various frequencies: delta (0.1 - 0.4 Hz), theta (4 - 8 Hz), alpha (8 - 12 Hz), beta (12 - 30 Hz), gamma (30 - 60 Hz), high gamma (60 - 120 Hz).

After the power bands have been extracted, we took the average power for each condition and compared them to other conditions. Since the epochs were based on the time to button press, each trial is of a different size. To work around this, each trial was cut to the length of the shortest trial in its condition, so every signal in a given condition had the same length.We also detected the spikes in the signal (**Fig 7**) and added the total number of spikes divided by the length to get the percentage of spikes, the average amplitude of each spike, and the average distance between them. This resulted in a total of 9 features per channel, and with 62 channels (channels 62 and 63 are removed for stimulation) we have 558 features per trial.

To test how separable the extracted features were, we performed a t-test on every condition against every other condition for each of the features individually and then with all of the features overall (**Fig 8**). We also visualized the features using a PCA plot and labeled the data according to the condition (**Fig 9**).

Finally, we tested if we can classify each stimulation condition solely on the neural features. We used a random forest classifier with 100 trees and trained on two-thirds of the data. We then extracted the feature importance by getting the weights of each of the features and consolidating them into total importance per feature and per channel.

3 Results

As observable in **Fig 5**, there was a large amount of noise in each band. This is because the power bands are oscillatory and if the phase of each signal is off, the average has a lot of spikes. To compensate for this, we plotted the moving power of each band as opposed to the raw average. In **Fig 6**, the signal was smoothed considerably and differences/similarities in the signals are easier to view. To have a more formal comparison, we used t-tests to compare if the data is similar to each other or not.

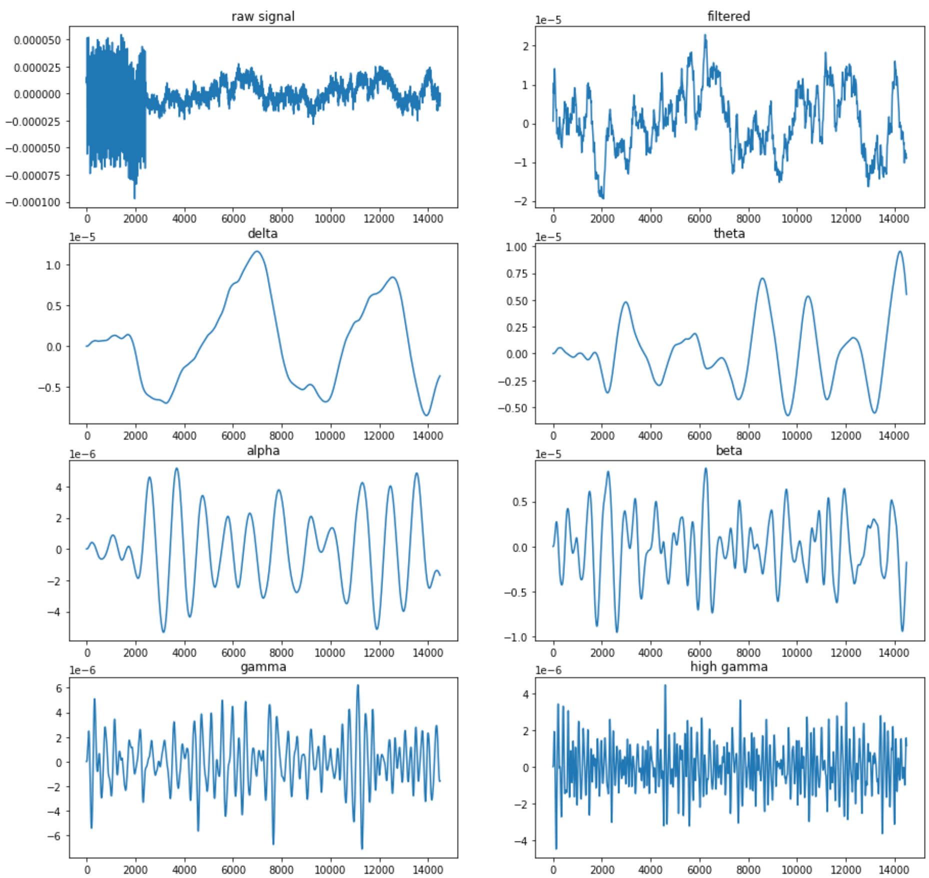

Figure 4: The full pipeline of the signal being deconstructed into different parts. Top left is the raw signal. Top right is the filtered signal after the stimulation artifact removal and various filters. The power bands are extracted from the filtered signal.

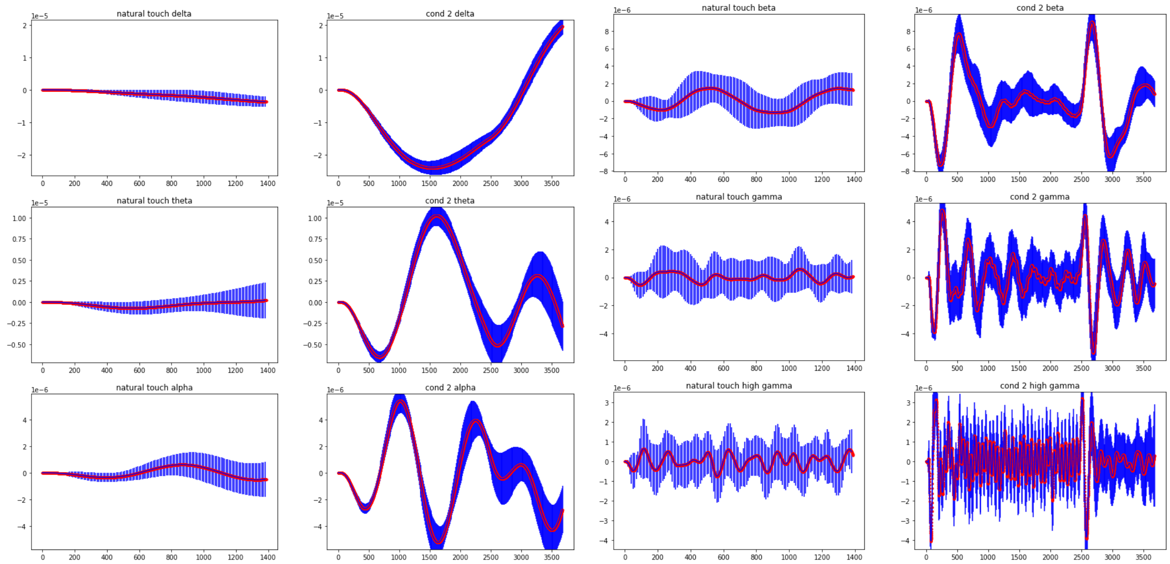

Figure 5: Average of the 6 power bands at electrode 61 over all of the trials of natural touch (condition -1) and condition 2. The red is the average signal, the blue is the variance.

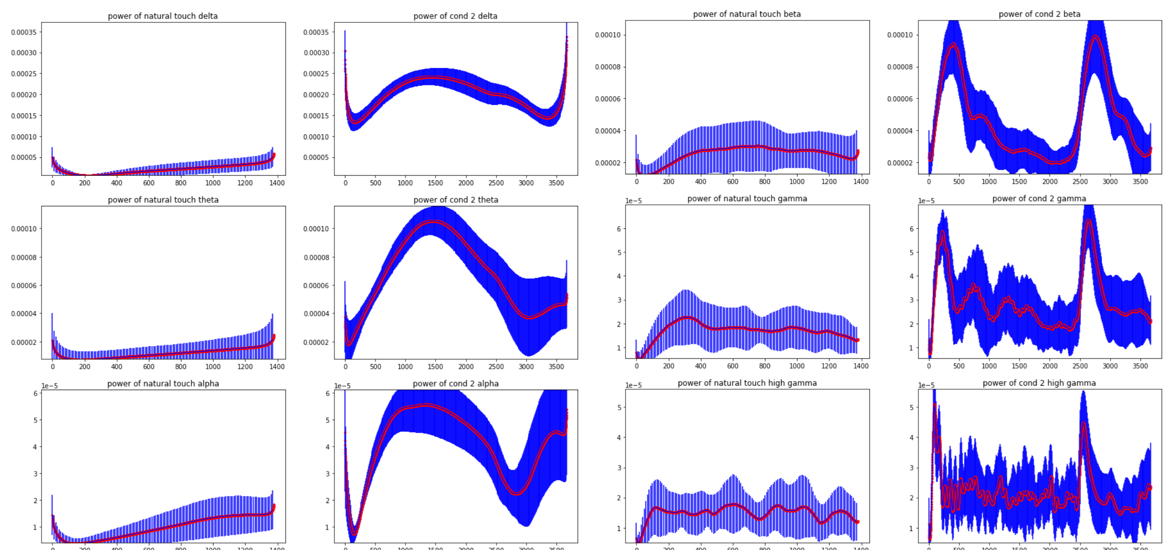

Figure 6: Sliding power with a window of 10 of the 6 power bands at electrode 61 over all of the trials of natural touch (condition -1) and condition 2. The red is the average signal, the blue is the variance.

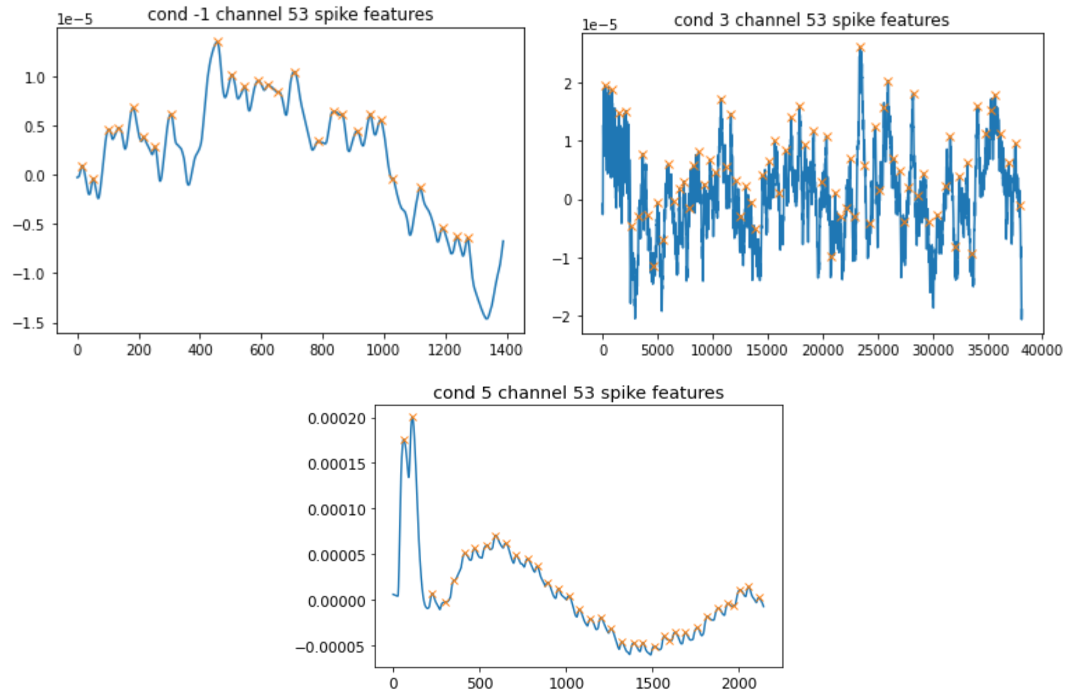

Figure 7: Examples of the spikes that are detected for the spiking features from three different conditions.

Based solely on the t-tests (**Fig 8**), none of the power bands seemed to discriminate between conditions as there are a lot of distributions that were not statistically significantly different from each other. However, the power bands were good at determining if the conditions had artificial stimulation or natural touch as most of the t-tests involving condition -1 are close to zero. The t-tests corresponding to the spike features showed that the spike features were a bit more distinguishable between subjects as much more of the matrix is close to zero. In fact, the average t-statistic of the confusion matrices of percentage of spikes and average distance between spikes were 0.018 and 0.016 respectively, much lower than the average t-statistic of the two most distinct power band features, gamma and high gamma, at 0.038 and 0.037 respectively. Overall, the average t-statistic of the spike features was 0.042 and the average of the power bands was 0.055.

The clustering of the conditions on the PCA plot (**Fig 9**) tells us that the features are distinct enough that given just the raw list of extracted features, a computer would know which condition it was with pretty good certainty. This is confirmed by the fact that we were able to achieve a 98.9% accuracy with the random forest classifier we trained.

To learn about how exactly the classifications were happening, we extracted the feature importance from the model(**Fig 10**). As visible by the bar graph of feature importance, the spike features were very important compared to the power bands. Also, the channels that were most important are in the top left corner, right along where the sensorimotor cortex is. This observation lines up with the neuroscience behind it, because the sensory regions of the brain should have the most defining activity in this touch task.

Seeing how important the spike features are for the model, we ran the model without them to see how the accuracy compares. With only the 6 power densities per channel, the classification accuracy drops to 91.9%. However, training the model with only the 3 spiking features results in an accuracy of 93.3%, indicating that the features together are what's most helpful for the model. Despite the spiking features being more important overall, the most important individual features were the beta, theta, and alpha power of channel 61. Clearly, something about the association between the spiking features with the power bands is what's unique about the conditions.

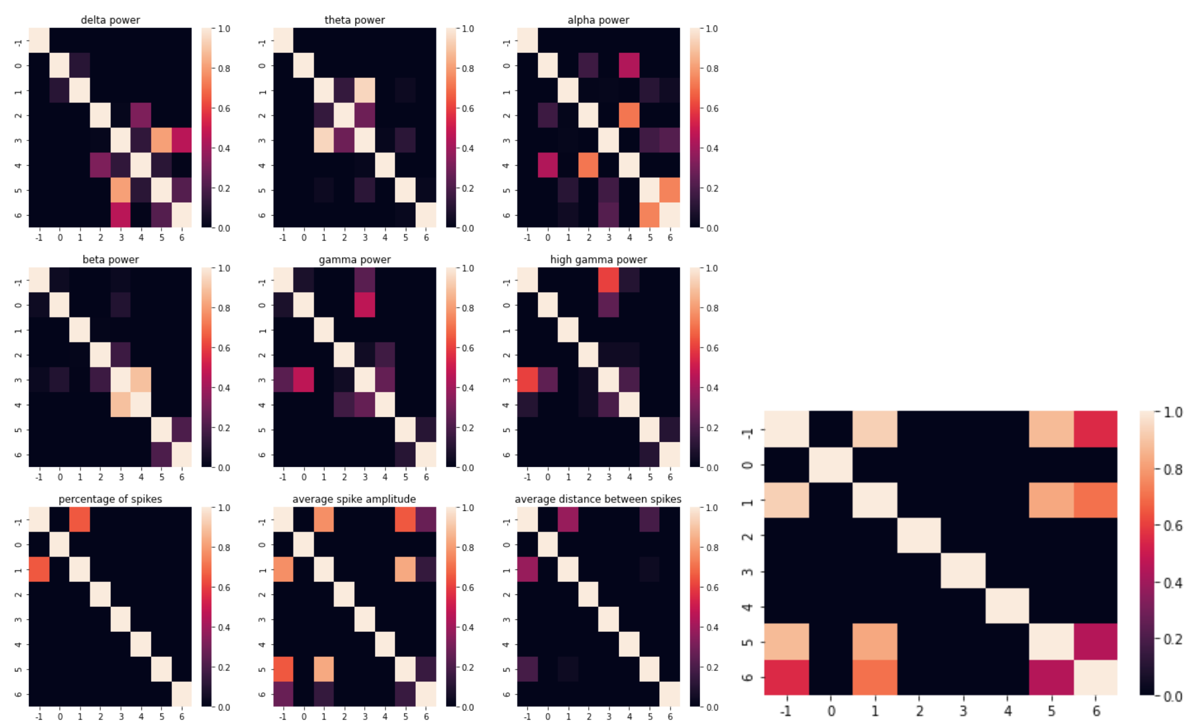

Figure 8: The left 9 graphs are the confusion matrices for each feature for t-tests across each condition. The right is the confusion matrix of the t-tests performed over the entire feature set.

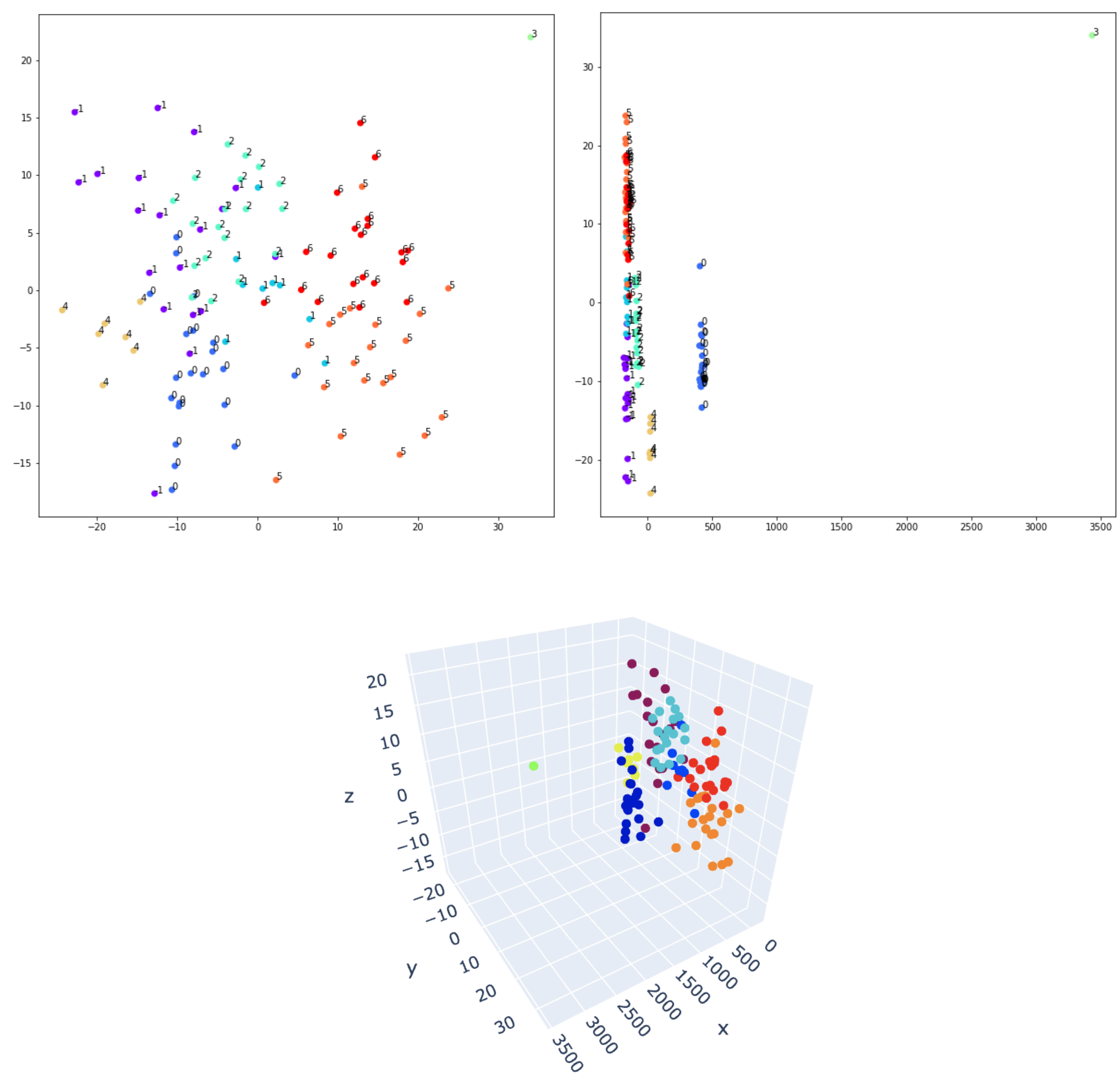

Figure 9: PCA plots visualizing each of the features with the color and label denoting which condition the trial corresponds to. The top 2 graphs are different sides of the 3d cube below.

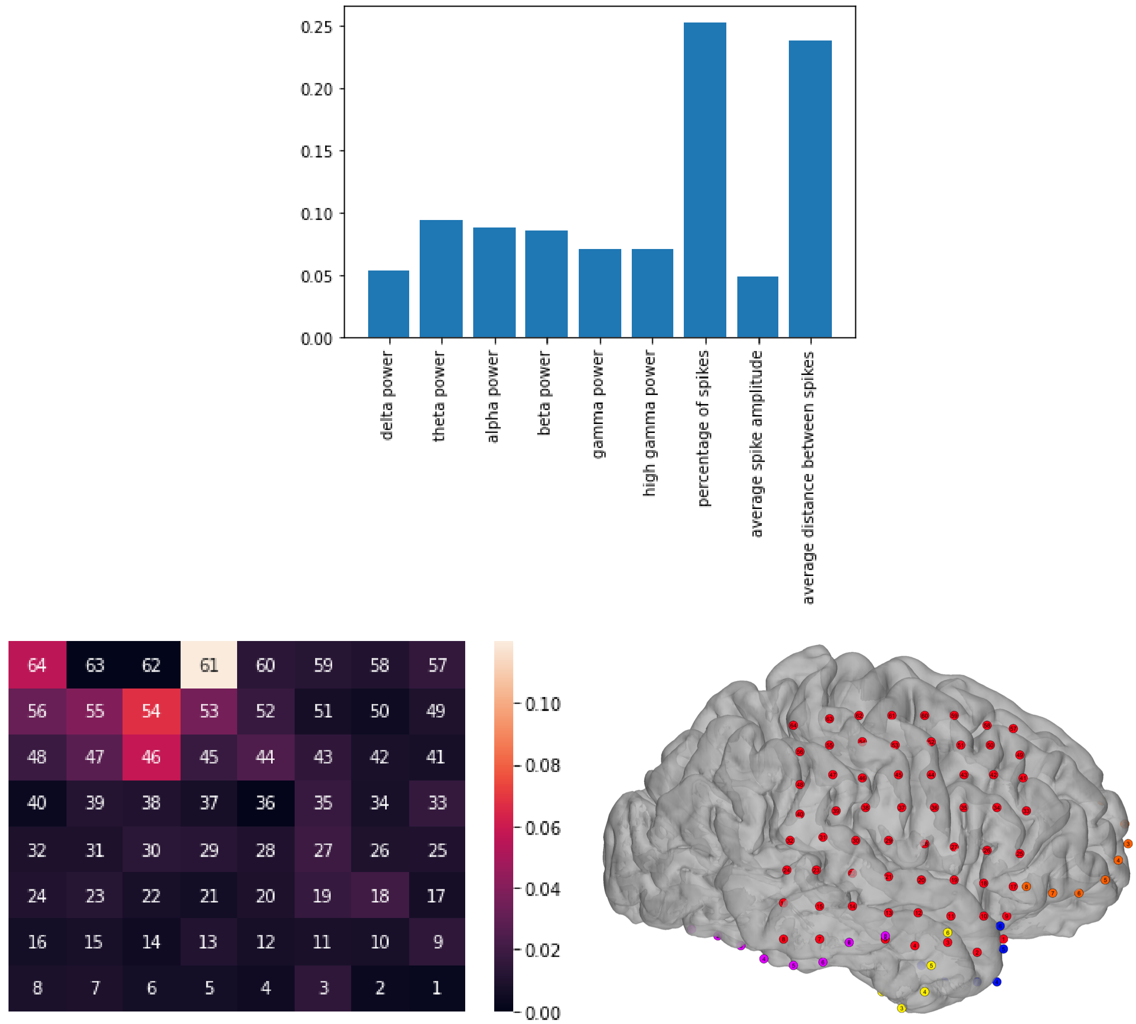

Figure 10: The top bar graph shows the weight that each feature holds on the model. The bottom left graph shows how much weight each channel holds on the model. Channels 62 and 63 are zero due to them being stimulation channels. The bottom right shows the location of the 8x8 grid on the subject's brain.

4 Discussion

We knew that DES is slower than natural touch **[6]**, but this project explores the processing differences between the two to find out what exactly is different between them. The main finding was that the spike features seem to be very important for the model and that the most important individual features were the beta, theta, and alpha power of channel 61. Since ECoG data typically doesn't pick up single unit spiking activity **[7]**, the meaning of the spike features is a bit ambiguous, especially since the model places such a high importance on them. It's most likely measuring how neighboring neurons spike together and isn't a really single spike but rather a collection of them. Also, as shown by the model accuracies, the model performs best with the spike features and the power bands together so it could be something about the association between the spiking features with the power bands that's unique about the different conditions. This feature extraction is significant because it gives us a way to represent the ECoG signals and we found that the conditions are not only different from each other, but also similar amongst themselves.

A limitation of this analysis is that since we had to match each signal in a condition to be the same length, we lose some potentially valuable information as the ends of the signals are cut off.

It is important to note that the channels that were deemed important (**Fig 10**) are also near the stimulation channels (channels 62 and 63). It's still debatable whether the significance is coming from the fact that the channels are on the sensory cortex or from the fact that it's right near the stimulation regions and there could be further work done to find out which one it is. Also, since there is a small lag in even the natural touch case for reacting to touch stimuli, it could be interesting to see if we could predict how fast someone would react to a stimuli so that we can time the stimulation accordingly in the neural prosthetic context.

From this project, we learned what features are most distinguishing between artificial versus natural touch stimulation, and this work informs future DES research where we can tweak the DES to try and modify those features and more effectively provide sensory feedback for motor prosthetics.

All code from this project can be found at **[8]**.

5 Acknowledgments

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