

EEG Correlates of Tactile Sensations

Research Report

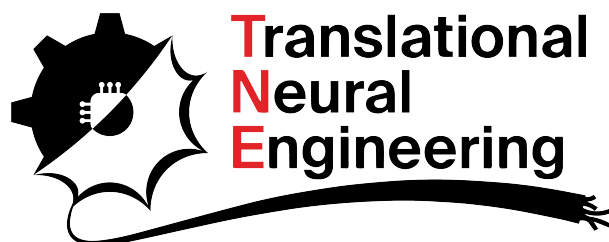
Yi-Chen Pai

Niccolò Venturini Degli Esposti

Supervisor: Leonardo Pollina

Professor: Silvestro Micera

EPFL



Abstract

This study explores the neural correlates of tactile sensations using EEG to understand how the brain processes varying levels of force and vibration. Participants were exposed to six combinations of tactile stimuli across six sessions, with EEG data collected via a 64-channel cap and analyzed using the MNE Python library. Key findings revealed distinct brain activity patterns in central-parietal regions, with stronger stimuli eliciting enhanced P200 and P300 components. These results offer insights for improving sensory feedback in prosthetics, paving the way for more lifelike and intuitive touch experiences through neural-based sensory technologies.

Acknowledgements

I would like to extend my sincere gratitude to my supervisor, Leonardo Pollina, and Professor Silvestro Micera for their invaluable guidance and support throughout this project. I also wish to thank my colleague Niccolò Venturini Degli Esposti in the lab for his collaboration and assistance, which contributed significantly to the success of this research. Additionally, I am deeply grateful to the Laidlaw Foundation for their generous support and commitment to fostering the development of future leaders, without which this opportunity would not have been possible.

Contents

1	Introduction	5
1.1	Background on Tactile Sensation and Receptors	5
1.2	Motivation for the Study	5
1.3	Study Objective	5
2	Methodology	6
2.1	Experimental Design	6
2.2	Experimental Procedure	6
2.3	EEG Data Acquisition	7
3	Preprocessing	8
3.1	Data Preparation	8
3.2	Event Processing and Epoch Creation	9
3.3	Artifact Removal and Signal Enhancement	9
3.4	Noise Detection and Interpolation	11
4	Data Analysis and Results	11
4.1	Grand Average Evoked Responses	11
4.2	Topographical Maps	11
4.3	ERP Components	13
4.4	Statistical Analysis	14
5	Discussion	14
5.1	Interpretation of Results	14
5.2	Implications for Prosthetics	15
5.3	Limitations	15
5.4	Future Directions	15
6	Conclusion	16

1. Introduction

1.1. Background on Tactile Sensation and Receptors

Tactile sensation is one of the most essential sensory experiences, allowing humans to interact with their environment and perform tasks requiring dexterity, such as grasping and manipulating objects[1]. The human skin is equipped with specialized mechanoreceptors that detect various types of touch, including pressure, vibration, and stretch. Four main types of mechanoreceptors contribute to tactile perception: Meissner's corpuscles, Merkel cells, Pacinian corpuscles, and Ruffini endings[2].

Meissner's corpuscles, located near the surface of the skin, are fast-adapting receptors sensitive to light touch and low-frequency vibrations. Merkel cells, also found close to the skin surface, are slow-adapting receptors that respond to sustained pressure and texture. Pacinian corpuscles, positioned deeper in the dermis, are fast-adapting receptors tuned to high-frequency vibrations and transient pressures, while Ruffini endings detect skin stretch and are slow-adapting receptors.

Understanding how these receptors process tactile information is crucial for comprehending how the brain encodes sensory inputs. Tactile signals are transmitted through the somatosensory pathway to the brain, where they are processed in regions like the primary somatosensory cortex (S1)[3]. Research into tactile processing can provide valuable insights into neural encoding and has significant implications for developing technologies like prosthetics, which aim to restore or mimic natural touch sensations.

1.2. Motivation for the Study

Understanding EEG correlates of tactile sensations is crucial for advancing prosthetic technologies, particularly in addressing issues such as phantom limb sensation (PLS), where individuals continue to feel the presence of a lost limb[4]. Restoring natural touch through sensory feedback in prosthetics can help alleviate PLS and improve the user's control and sense of body ownership[5]. However, current prosthetic devices lack intuitive, real-time feedback[6].

By studying how the brain processes tactile stimuli, especially with varying force and vibration levels, this research aims to fill gaps in understanding the neural encoding of complex sensations. These insights can contribute to the development of more sophisticated prosthetic devices and sensory augmentation systems, offering improved functionality and a better quality of life for amputees.

1.3. Study Objective

The primary objective of this study is to investigate the neural correlates of tactile sensations by analyzing brain responses to different combinations of force and vibration stimuli using electroencephalography (EEG)[7]. By understanding how the brain processes these sensations, the study aims to contribute to the development of advanced prosthetic devices capable of providing natural, intuitive sensory feedback.

The experimental setup involves the use of a 64-channel EEG cap connected to an ANT Neuro amplifier and a tactile stimulator (TouchDIVER), which delivers controlled tactile stimuli to participants. Six combinations of force and vibration levels are applied, and EEG signals are recorded during the process to capture the brain's response to each

stimulus. Preprocessing techniques are employed to clean the data, followed by detailed analysis to identify event-related potentials (ERPs) that reflect neural activity associated with the tactile inputs[8].

2. Methodology

2.1. Experimental Design

Participants: Five able-bodied participants were recruited for the study. All participants were briefed on the purpose of the experiment, which focused on investigating tactile stimulation and EEG correlates. The inclusion criteria required participants to be in good health and without any neurological disorders.

Materials and Setup: The experiment utilized a 64-channel EEG electrode cap and amplifier (ANT Neuro eego™) paired with a TouchDIVER¹ device for tactile stimulation. The EEG cap followed the international 10/20 positioning system, with CPz used as the reference and AFz as the ground electrode. Electrode impedance was maintained below 25 kΩ. For tactile stimulation, participants wore the TouchDIVER glove, which applied both force and vibration stimuli to the fingertips of their right hand.

The TouchDIVER was connected via Arduino, allowing the delivery of two distinct force levels (minimum and maximum) and three vibration conditions (no vibration, low-frequency, and high-frequency). The minimum force was defined as the lowest pressure at which participants could consistently perceive the tactile stimulation, and the maximum force was set as the highest deliverable force by the device (up to 5 N). These force thresholds were calibrated individually for each participant to ensure perceptibility and distinction.

In addition to force feedback, the device was equipped to provide vibration feedback. The three vibration conditions included no vibration (baseline), low-frequency vibration (modulated at 3 Hz), and high-frequency vibration (modulated at 7 Hz). The vibration modulations were designed to simulate various tactile textures or sensations, offering a comprehensive set of stimuli combinations involving force and vibration.

The TouchDIVER's tactile feedback system was customized using 3D-printed adapters for each participant based on their individual finger measurements. Similarly, the EEG cap was fitted using individualized head measurements to ensure proper electrode contact and minimize impedance.

2.2. Experimental Procedure

Introduction to Stimuli: Prior to the main experiment, participants were familiarized with six different tactile sensations that combined both force and vibration conditions. These included No Frequency, Low Frequency, High Frequency, and combinations with both Low and High Force. During this pre-test phase, participants were required to correctly identify 80% of the stimuli to proceed to the main experiment. This ensured that participants were sufficiently familiar with the tactile stimuli to make reliable classifications during the experimental sessions.

Main Experiment: The experiment consisted of six sessions, each containing 90 randomly ordered stimuli, resulting in a total of 540 stimuli per participant. Each trial

¹<https://weart.it>

began with a fixation cross on the screen for a randomly varying time interval of -1 to 2 seconds. Following this preparation phase, tactile stimuli combining force and vibration were presented to the participants, followed by a 3-second break. Random classification tasks were embedded into each session to ensure participant engagement, requiring them to classify the combination of force and vibration they had just experienced. This interactive setup maintained focus and provided valuable behavioral data on how participants perceived and distinguished between the different stimuli.



Figure 1: A participant undergoing EEG data acquisition while responding to tactile stimuli. The participant wears a 64-channel EEG cap, and real-time data is captured on the connected monitor. The experimental setup includes multiple screens for stimuli presentation and EEG signal monitoring.

2.3. EEG Data Acquisition

Signal Capture: EEG signals were recorded throughout the experiment at a sampling rate of 1000 Hz. During preprocessing, the data were down-sampled to 256 Hz to reduce computational complexity while maintaining signal integrity. Each session had a total duration of approximately 54 minutes. Participants wore earplugs during the experiment to block out the sound of the TouchDIVER motor, thus minimizing the risk of auditory predictions influencing their responses. Additionally, participants were instructed to remain relaxed, avoid unnecessary movement, and minimize eye blinks to prevent artifacts in the EEG data. Impedance checks were routinely conducted to ensure the quality of EEG signals.

3. Preprocessing

3.1. Data Preparation

Band-Pass Filtering: The EEG data was band-pass filtered in the range of 0.5 to 60 Hz. This range was selected to retain the signal components of interest while minimizing the influence of artifacts. Lower frequencies (below 0.5 Hz) typically contain drift and slow non-neuronal activity, while higher frequencies (above 60 Hz) can be dominated by muscle artifacts (e.g., EMG signals) and external electrical noise (50/60 Hz power line noise). Filtering within this range helps to isolate relevant EEG components, including common neural rhythms like delta, theta, alpha, and beta bands, while reducing contamination from non-brain-related activities.

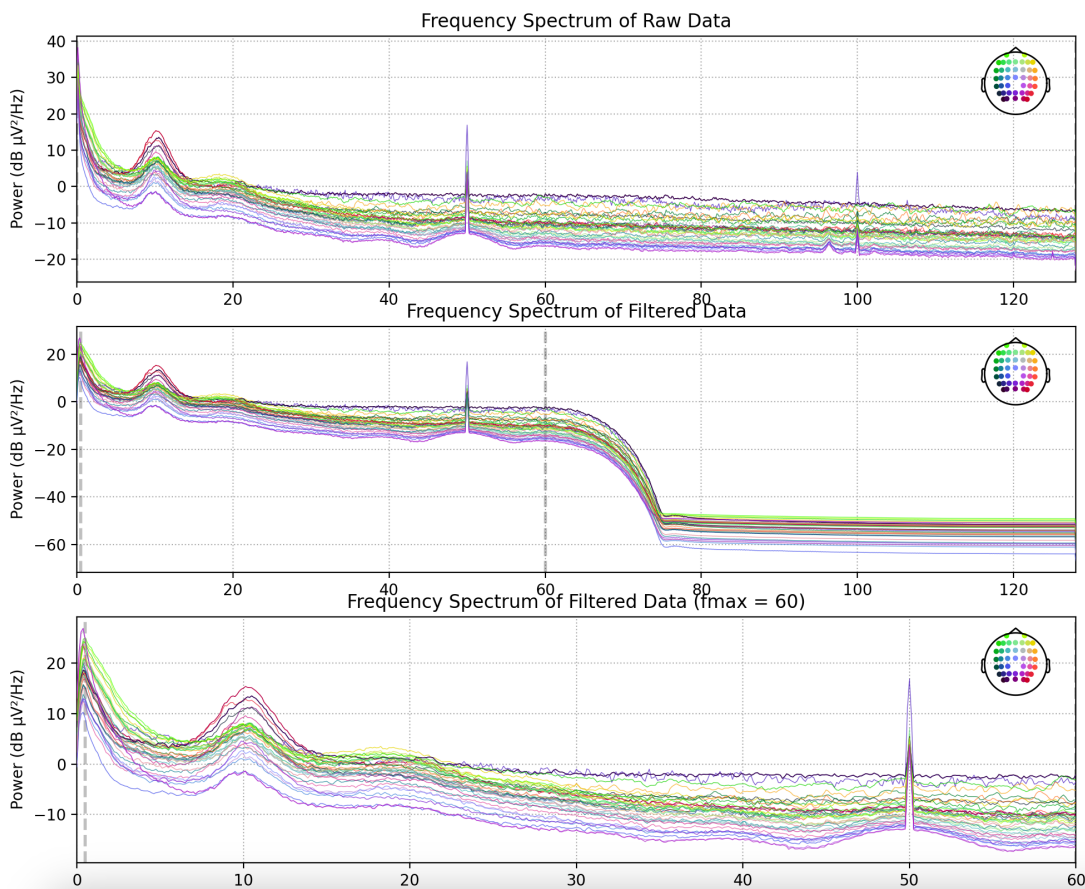


Figure 2: Frequency spectrum analysis of raw and filtered EEG data. The top plot shows the raw data with evident noise components, including power line noise at 50 Hz. The middle plot represents data after applying a band-pass filter from 0.5 to 60 Hz, reducing high-frequency artifacts. The bottom plot further zooms in on the filtered data ($f_{\max} = 60$ Hz) for better visibility of relevant frequency bands.

Channel Reordering: The EEG channels were reordered to match the standard 10-20 system layout, ensuring consistent spatial mapping across subjects. Channels located on the periphery of the scalp, which are less likely to capture neural activity of interest (e.g., external noise or irrelevant artifacts), were removed from further analysis. This process included the exclusion of bipolar (BIP) channels and eye-related (EOG) channels.

The reordered dataset was then saved for further analysis, ensuring that only the relevant scalp channels were retained for subsequent steps.

3.2. Event Processing and Epoch Creation

Event Relabeling: Accurately relabeling events in the EEG data was a critical step to ensure that each trial followed the proper sequence of actions, including tactile stimuli, cues, and rest periods. In this step, the raw data's annotations were carefully reviewed and corrected as needed to align with predefined event types. 'Cue' events marked the beginning of each trial, and the entire event sequence was systematically organized to guarantee that each stimulus was appropriately labeled. Irrelevant events, such as system markers or boundaries, were removed to reduce noise and avoid confusion in the analysis process.

For each trial, the descriptions and onset times of events were extracted, and trials were created by grouping related events. The relabeling ensured that the specific type of tactile stimulus applied during each trial was correctly represented. After relabeling, a verification step was performed to confirm that the event sequences matched the structure outlined in the experimental design. This ensured that the sequence of relabeled events was accurate, thereby minimizing the risk of errors in later stages.

Sequence Verification: After relabeling, each trial's sequence of events was checked to ensure that the expected structure was maintained. This process involved reviewing the event markers and confirming the correct order of stimuli and responses. Any discrepancies found in the trial structures, such as misplaced markers or incorrect event labels, were corrected to maintain consistency throughout the dataset.

Segmentation: With the relabeling and verification complete, the continuous EEG data was segmented into epochs based on the tactile stimuli. Each epoch was defined as a window of neural activity starting 1 second before the stimulus and extending 5 seconds after. This segmentation was chosen to capture both preparatory neural processes and the brain's response to the stimuli.

To ensure consistency across trials, clear start and end times were defined for each epoch. This allowed for uniform time-locked windows for each tactile stimulus, facilitating comparison across subjects and trials. The EEG data was then cropped to isolate only the relevant windows around the stimuli and cues.

In cases where there were variations in trial durations or event timings, adjustments were made to align the end times with the average rest period duration. This ensured uniformity across all trials, which is essential for accurate comparisons of neural responses to stimuli.

Finally, a slight temporal shift (approximately 100 ms) was applied to account for timing discrepancies between the stimuli and EEG data acquisition, ensuring precise alignment between the stimulus and the neural response.

3.3. Artifact Removal and Signal Enhancement

Independent Component Analysis (ICA): Independent Component Analysis (ICA) was employed to identify and remove artifacts from the EEG data, such as those generated by eye blinks and muscle movements. The ICA model was applied to the preprocessed data to decompose the EEG signals into independent components, some of which represented neural signals and others noise. The explained variance was assessed to quantify

how much of the signal could be attributed to each component.

The independent components were manually inspected using scalp topography maps to identify those corresponding to non-neural artifacts, such as eye movements and muscle activity. These artifact components were excluded from the dataset, ensuring that only the relevant neural activity was retained. This process significantly reduced noise and enhanced the clarity of the neural signals for further analysis. Once ICA was applied, the cleaned data was saved for future use, free from the contamination of unwanted artifacts.

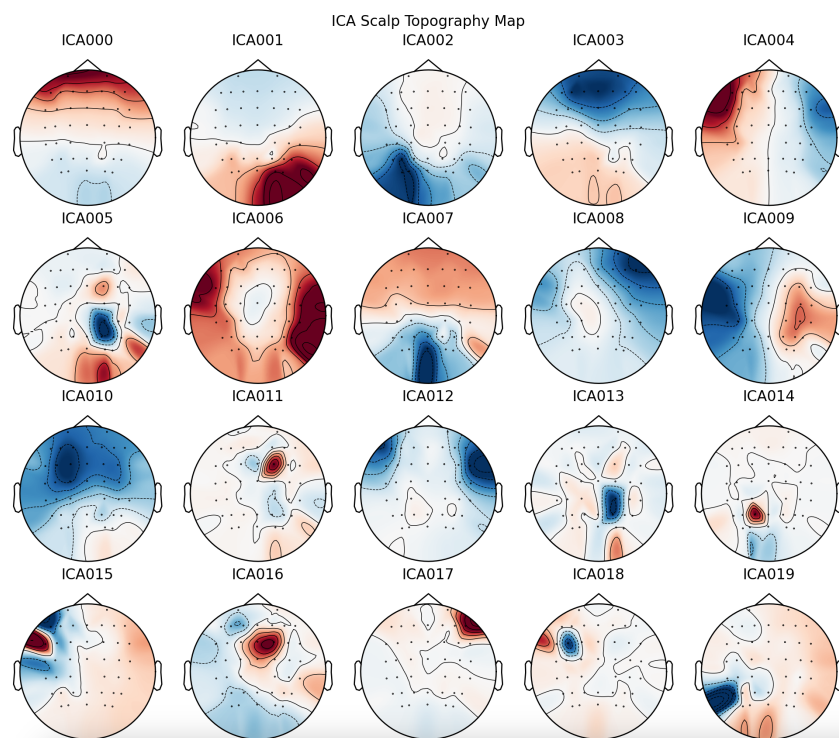


Figure 3: ICA scalp topography maps for different independent components. In this figure, IC001 and IC004 exhibit patterns commonly associated with non-neural artifacts. IC001 shows strong frontal activation, resembling eye-blink artifacts, while IC004 displays lateralized activity indicative of saccadic eye movements. These components were manually identified as artifacts and were thus removed from the dataset to ensure the quality of the neural signals used in subsequent analysis.

Re-referencing: After applying ICA, the EEG data was re-referenced using the common average reference (CAR) technique. This approach involves calculating the average signal across all electrodes and subtracting this average from each electrode's individual signal. CAR reduces the influence of widespread artifacts, such as environmental noise or global head movements, while enhancing the sensitivity to localized neural activity. This technique improved the accuracy of the data, especially in detecting localized brain dynamics. The re-referenced data was saved for use in subsequent analyses.

Baseline Correction: To account for any slow drifts or baseline shifts in the data, baseline correction was performed. The baseline period was defined as the interval from -0.2 to 0 seconds, just before each stimulus. By subtracting the mean of this baseline period from the entire epoch, any slow-frequency noise or drift was minimized. This correction ensured that the neural responses measured after stimulus onset were not affected by non-neural shifts, thereby providing a more accurate representation of the brain's activity in response to the stimuli.

3.4. Noise Detection and Interpolation

Channel-Specific Artifact Detection: The next step involved identifying noisy channels on a per-epoch basis. For each epoch, the data from each channel was examined to detect large deviations from the expected signal. A maximum threshold was set, and any channel with a signal exceeding this threshold was flagged as containing an artifact. If the number of noisy channels in an epoch exceeded a predefined threshold, the entire epoch was marked for rejection. This allowed for the detection of epochs where the noise was too widespread for interpolation to be effective.

For epochs with only a few noisy channels, those specific channels were marked for interpolation. This process involved replacing the noisy data from the affected channels with values estimated from the surrounding channels using spatial interpolation techniques. Interpolation ensures that the overall signal quality is maintained while preserving as much of the clean data as possible. By applying this selective approach to artifact detection, only channels with significant noise were corrected, while unaffected channels retained their original signal.

Data Interpolation Techniques: In epochs where only a small number of channels were identified as containing artifacts, interpolation was performed to reconstruct the signal in these noisy channels. The interpolation method used spatial information from neighboring channels to estimate the missing or noisy data. This method helps recover the data from bad channels without compromising the integrity of the entire epoch. Once the interpolation was complete, the cleaned epochs were concatenated to form a complete dataset for further analysis.

Channels that had been marked as “bad” were reset after interpolation to ensure that the cleaned data could be treated as reliable for the next steps in the analysis pipeline. This process allowed for the correction of minor artifacts while preserving the structure of the neural data.

Finally, the cleaned and interpolated data was saved, ready for further analysis steps such as z-scoring and epoch averaging. By applying these techniques, the overall quality of the EEG data was significantly enhanced, enabling more reliable and interpretable results.

4. Data Analysis and Results

4.1. Grand Average Evoked Responses

The grand average evoked response for each condition (low force - no frequency, low force - low frequency, low force - high frequency, high force - no frequency, high force - low frequency, high force - high frequency) was computed by averaging the evoked responses across trials for this specific condition. The grand average represents the brain’s overall response to this condition, consolidating data from all trials under this specific stimulation.

4.2. Topographical Maps

The topographical maps for each condition (low force - no frequency, low force - low frequency, low force - high frequency, high force - no frequency, high force - low frequency, high force - high frequency) were generated to visualize the spatial distribution of brain

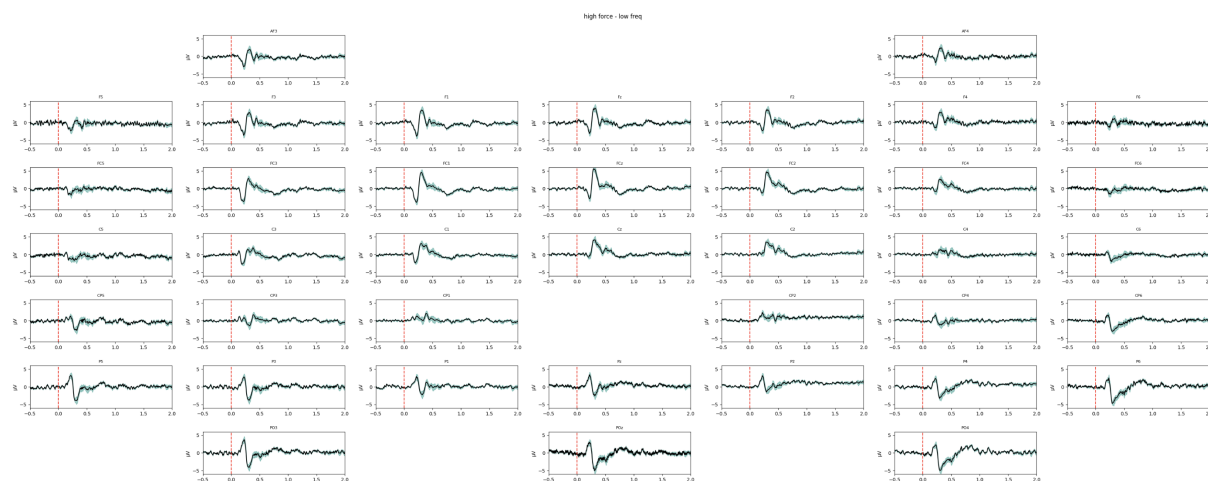


Figure 4: Grand average evoked response for the high-force, low-frequency condition across all channels. The red dashed line at 0 seconds represents stimulus onset, and the shaded area shows the standard error of the mean (SEM).

activity at specific time points of interest. These maps provide insight into the differences in neural activation patterns across the scalp for the various force and frequency combinations.

In Figure 5, the brain’s activity is displayed at key time points—50 ms, 60 ms, 80 ms, 100 ms, 140 ms, 150 ms, 200 ms, 240 ms, 270 ms, 300 ms, 350 ms, and 500 ms—across all six conditions. These time points were chosen based on significant events observed in the grand averages. The figure shows how neural activation evolves over time and across different force and frequency levels, highlighting variations between low-force and high-force conditions.

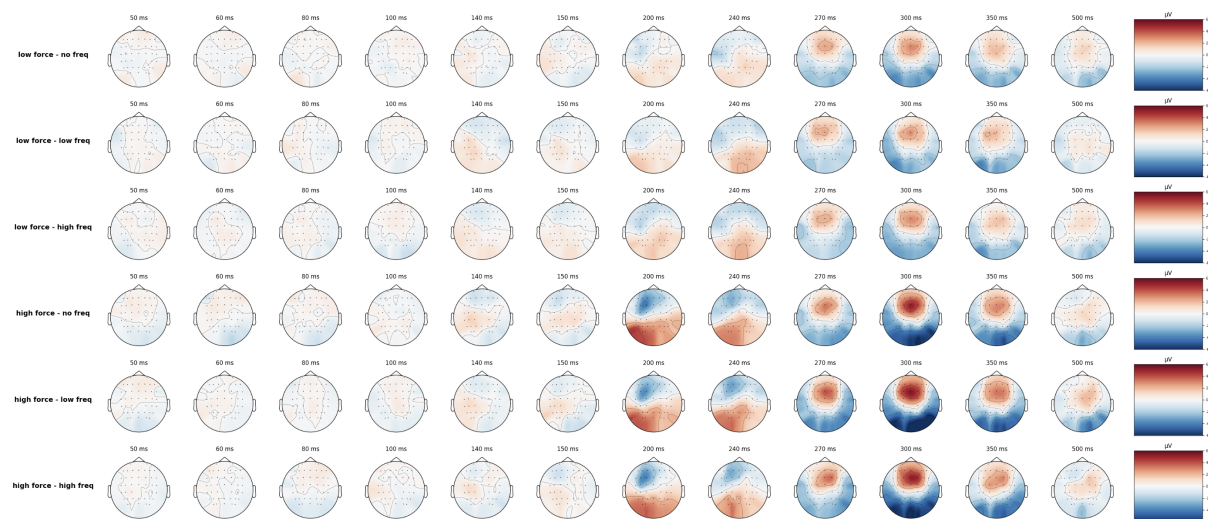


Figure 5: Topographical maps of brain activity at selected time points (50 ms to 500 ms) for each condition. Each row represents a condition, and each column represents a specific time point. Conditions include low-force and high-force combinations with varying frequency levels.

By comparing the spatial distributions, clear distinctions in brain activity between low-force and high-force stimuli are evident, particularly in the central and parietal re-

gions. High-force stimuli tend to show broader and stronger activation across the parietal areas, especially during later time points (200 ms onwards). In contrast, low-force conditions show more localized activation patterns. These differences in spatial distribution further corroborate the findings observed in the grand average evoked responses.

4.3. ERP Components

Spatial Distribution of Brain Activity:

To visualize the spatial distribution of brain activity, topographical maps were generated at two key time points: 200 ms and 300 ms, focusing on electrodes F3 and PO3, which represent the frontal and parietal regions, respectively. These maps allow us to compare neural activation across different conditions, including variations in force and frequency.

At 200 ms, as shown in Figure 6, noticeable activation is observed in both the parietal (PO3) and frontal (F3) regions across the conditions. This early activation indicates that the stimuli elicit significant brain responses in these regions.

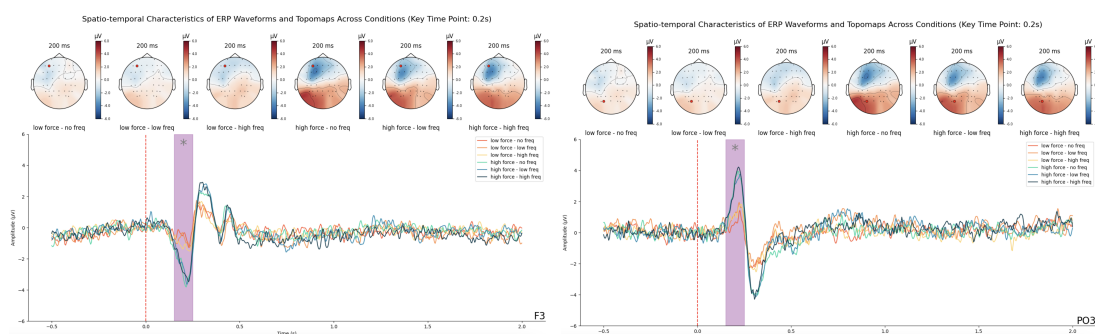


Figure 6: Topographical maps at 200 ms for electrodes F3 (left) and PO3 (right) showing brain activity across conditions.

At 300 ms, the maps shown in Figure 7 illustrate continued neural activation in the frontal (F3) region across all conditions, with sustained activity in the parietal (PO3) area. This suggests that cognitive evaluation and processing of the stimuli are ongoing at this later stage.

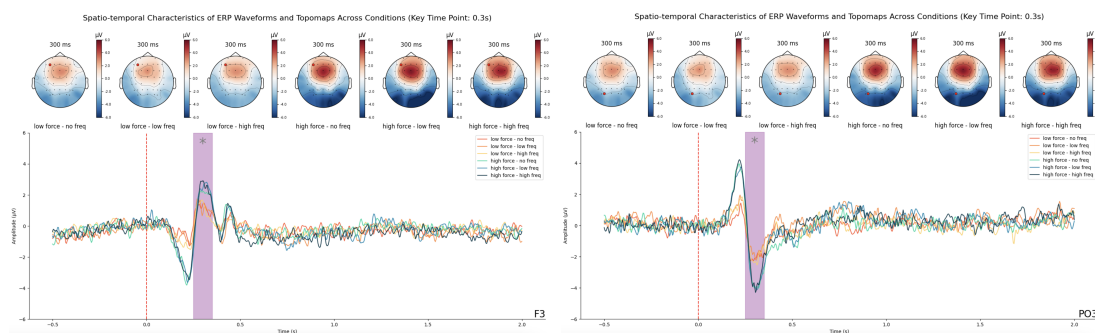


Figure 7: Topographical maps at 300 ms for electrodes F3 (left) and PO3 (right) showing brain activity across conditions.

The topographical maps for these two time points demonstrate the differences in neural activation patterns across conditions, indicating that frontal and parietal regions are key areas involved in processing the tactile stimuli.

4.4. Statistical Analysis

Comparison Across Conditions:

The statistical comparison between low-force and high-force conditions was performed by grouping the grand averages of evoked responses across the different combinations. Two groups of conditions were analyzed: Group 1, consisting of low-force stimuli, and Group 2, consisting of high-force stimuli. The grand averages for each group were computed by averaging across all conditions within each group, followed by calculating the standard error of the mean (SEM) to assess variability.

Figure 8 illustrates the grand averages and corresponding SEMs for both groups. The grand averages were compared across the entire time window, focusing on key moments of interest. The shaded regions represent the variability in the evoked responses across channels, with distinct differences observed between the two groups.

Significant differences were noted, particularly in the time windows around 200 ms (P200) and 300 ms (P300). These windows reflect early sensory processing and higher-order cognitive responses, respectively. The high-force conditions consistently exhibited stronger neural responses compared to the low-force conditions, particularly in these time windows.

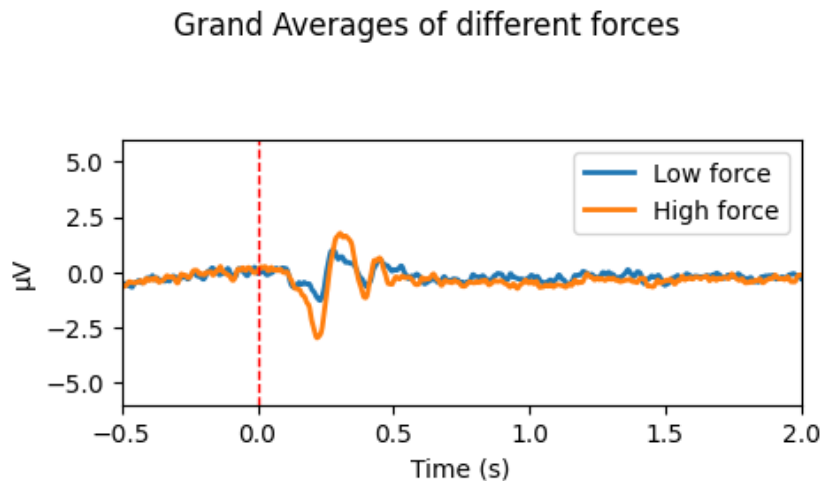


Figure 8: Statistical comparison of grand averages between low-force and high-force conditions. The shaded areas represent the standard error of the mean (SEM), showing variability across the channels.

This analysis demonstrates that force levels significantly modulate neural activity, with high-force conditions eliciting more robust brain responses, particularly in the mid and late time windows. These findings support the notion that tactile force influences both sensory and cognitive processing of stimuli.

5. Discussion

5.1. Interpretation of Results

The results from this study contribute to the understanding of how the brain processes tactile stimuli through neural responses captured via EEG. The grand averages and event-

related potentials (ERPs) elicited across varying conditions of force and vibration levels demonstrated distinct patterns of neural activity. Particularly, the N200 and P300 components reflected strong responses to high-intensity stimuli, aligning with previous research that highlights the sensitivity of these components to tactile input. These findings suggest that the brain differentiates between force and vibration levels early in the sensory processing stages, revealing that both the amplitude and temporal characteristics of these signals play critical roles in encoding tactile stimuli.

The activation patterns observed across central and parietal regions provide evidence that different cortical regions are engaged in the processing of tactile information, and force intensity significantly influences the brain's response. This supports previous literature, which underscores the importance of somatosensory feedback in how the brain interprets tactile sensations, a key aspect in human-object interaction and prosthetics research.

5.2. Implications for Prosthetics

This study's findings hold potential implications for the development of more sophisticated sensory feedback systems in prosthetics. By identifying specific neural signatures related to tactile force and vibration, these results could be applied to create prosthetic devices that offer more nuanced sensory feedback, emulating natural touch. The ability to elicit precise neural responses through controlled tactile stimuli could help in developing prostheses that provide users with a more natural and effective means of interacting with their environment.

In particular, incorporating vibration and force stimuli into prosthetic feedback systems may replicate the experience of touch for amputees, thereby restoring some of the lost sensory experiences following limb amputation. Leveraging these neural correlates could enhance the precision of prosthetic control, increasing both functionality and the user's sense of embodiment.

5.3. Limitations

Several limitations were encountered during the course of this research. First, the sample size was relatively small, consisting of only five able-bodied participants. While the findings provide valuable insights, a larger sample size would allow for more robust statistical analysis and generalizability of results. Additionally, technical constraints with the EEG equipment limited the precision of the data collection. Future studies may benefit from improved equipment or additional methodologies such as combining EEG with other neuroimaging techniques like fMRI to obtain a more comprehensive picture of neural processing during tactile stimulation.

5.4. Future Directions

To further extend the understanding of tactile encoding in the brain, future research should consider exploring other types of tactile stimuli, including temperature or more complex patterns of vibration and force. Additionally, incorporating a broader range of EEG analysis techniques, such as advanced time-frequency analysis or connectivity measures, could provide deeper insights into the temporal and spatial dynamics of brain responses to tactile input.

Moreover, this research could be expanded to include individuals with sensory impairments, such as amputees using prosthetic limbs. By studying how these neural correlates manifest in different populations, it may be possible to develop more targeted interventions to enhance the design of prosthetic devices. Finally, continued investigation into the role of P200 and P300 in sensory processing will be crucial for improving our understanding of the cognitive and perceptual aspects of tactile stimuli.

6. Conclusion

Summary of Key Findings:

This study has provided valuable insights into the neural processing of tactile stimuli, particularly in relation to force and vibration. By examining the event-related potentials (ERPs) and grand averages across different conditions, distinct patterns of brain activation were observed in both central and parietal regions. The P200 and P300 components demonstrated clear responses to variations in tactile stimuli, with high-force stimuli eliciting stronger neural responses. These findings indicate that both force and vibration play crucial roles in how the brain encodes and processes tactile information.

The research highlights the importance of these neural markers in sensory perception and opens up further possibilities for understanding the underlying mechanisms of touch. Overall, the results contribute to the growing body of knowledge on tactile sensation and neural activity.

Final Thoughts on Applications:

The findings from this study offer significant implications for the development of sensory feedback systems in prosthetic technology. By identifying specific neural signatures linked to force and vibration, the research provides a foundation for creating more naturalistic and responsive prosthetic devices. These devices could use tactile feedback mechanisms to enhance the user's interaction with their environment, potentially restoring the sensation of touch for amputees.

Additionally, this work contributes to a broader understanding of how the brain processes sensory information, which may influence the design of future technologies that rely on neural interfaces, such as brain-computer interfaces (BCIs) and virtual reality systems. The integration of tactile feedback in these fields could lead to more immersive and intuitive user experiences, with a wide range of applications in rehabilitation, human augmentation, and beyond.

References

- [1] Luis Vargas et al. “Resembled Tactile Feedback for Object Recognition Using a Prosthetic Hand”. In: *IEEE Robotics and Automation Letters* 7 (Oct. 2022), pp. 10977–10984. DOI: 10.1109/lra.2022.3196958.
- [2] Astrid M.L. Kappers and W.M. Bergmann Tiest. *Tactile and Haptic Perceptual Organization*. Oxford University Press, July 2014. DOI: 10.1093/oxfordhb/9780199686858.013.002.
- [3] Hideaki Onishi et al. “Neuromagnetic activation of primary and secondary somatosensory cortex following tactile-on and tactile-off stimulation”. In: *Clinical Neurophysiology* 121 (Apr. 2010), 588–593. DOI: 10.1016/j.clinph.2009.12.022. URL: <https://www.sciencedirect.com/science/article/pii/S1388245709007925>.
- [4] Ivan Molton. “Phantom Limb Pain”. In: *The Corsini Encyclopedia of Psychology* (Jan. 2010), pp. 1–1. DOI: 10.1002/9780470479216.corpsy0674.
- [5] Aidan D. Roche et al. “Upper limb prostheses: bridging the sensory gap”. In: *Journal of Hand Surgery (European Volume)* 48 (Jan. 2023), pp. 182–190. DOI: 10.1177/17531934221131756.
- [6] Llewellyn Dsa et al. “A Vibrotactile Sensory Feedback System for Prosthetic devices”. In: *TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON)* 17 (Oct. 2019), pp. 2449–2453. DOI: 10.1109/tencon.2019.8929504.
- [7] Nidhi Gupta and Gyaninder Singh. “Electroencephalography-based monitors”. In: *Journal of Neuroanaesthesiology and Critical Care* 02 (Dec. 2015), pp. 168–178. DOI: 10.4103/2348-0548.165030.
- [8] C Genna et al. “Long-latency components of somatosensory evoked potentials during passive tactile perception of gratings”. In: *PubMed* (Aug. 2016). DOI: 10.1109/embc.2016.7591030.