An AI -Based Model for Texture Classification from Vibrational Feedback: Towards Development of Self-Adapting Sensory Robotic Prosthesis

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Abstract— **This paper presents a novel method of tuning vibration parameters to elicit specific perceptions of texture using vibration artefacts detected in EMG signals. Though often used for prosthetic control, sensory feedback modalities like vibration can be used to convey proprioceptive or sensory information. Literature has shown that the presence of sensory feedback in prosthesis can improve embodiment and control of prosthetic devices. However, it is not widely adopted in daily prosthesis use, due in large part to the daily change in perception and interpretation of the sensory modality. This results in daily parameter adjustments so that sensory perception can be maintained over time. A method therefore needs to be established to maintain perception generated by modalities like vibrations. This paper investigates modulating the vibration parameters based on how the vibrations dissipate in the surrounding tissue from the stimuli. This is with the aim of correlating dissipation of vibration to specific perceptions of texture. Participants were asked to control vibration motor parameters to elicit the perception of three different grades of sandpaper, provided to them for reference. Once the vibration parameters were chosen a CNN algorithm identified and categorized the artefact features along equidistantly spaced EMG electrodes. Participants were asked to repeat this experiment on three separate days and on the fourth was asked to complete a texture identification task. The task involved identifying the texture of the sandpaper based on their previously chosen parameters and compared the results to tuning against an AI-based algorithm using the dissipation of the vibration artefacts.**

Keywords—Vibrations, Artefacts, Dissipation, Electromyography, Prosthetics, Adaptive feedback, Robotics, Sensory substitution, CNN.

I. INTRODUCTION

Through technological advancements in sensory feedback, both prosthetic users and able-bodied individuals are able to feel a variety of tactile information from the external environment [1-3]. The inclusion of sensory feedback in prosthesis has been shown in literature to improve grasping, object recognition, embodiment, and reduce instances of neuropathic pain [4-8]. It was also found that accurate and intuitive sensory feedback was a high priority for prosthesis users. Peerdman et al conducted a study that determined that easy, intuitive, and adjustable feedback was a priority in the continued use of non-invasive prosthesis [9]. Similarly, Cordella et al found that integration of a tactile sensorization system that provided accurate sensory feedback was important to prosthesis users [10].

Vibrational feedback is one of the most commonly used modalities for sensory feedback and can be used to establish discernable patterns of texture, which has been shown to allow prosthesis users to adjust and manipulate objects more effectively [11]. Despite its success, vibrational feedback is often underutilized in prosthesis due to the variability in perception of the stimuli. For example, vibration parameters can be adjusted so that individuals perceive the feeling of moving their hand along specific surfaces [11, 12], however, the same parameters may elicit a different perception the following day or over time [13]. Consequently, daily fine-tuned adjustments to the parameters are made to maintain the same level of perception, preventing long term adoption of sensory feedback in prosthesis. Daily changes in weight, hair, body temperature, and other physical attributes are factors that can affect the stimuli and is therefore believed to be the cause of the variations in perceptions [13]. These physical attributes can also vary significantly between individuals and thus prevents the adoption of a ubiquitous system or settings that can maintain accurate, long-term sensory feedback for users [13, 14]. It is therefore important to establish a relationship between subjective processes like perception and the physiological response from vibration stimuli.

Previous work conducted has found that vibrations generated distinct artefacts in the frequency spectrum of electromyography (EMG) signals. These artefacts are often sensitive enough to detect changes in the physiological state of individuals and produce unique trends of vibration magnitude when monitored along the biceps [15]. These dissipation trends are unique to the individual and do not vary greatly over time.

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Both machine learning and deep machine learning techniques, such as convolutional neural networks (CNN), have been utilized in pattern recognition of features from EMG activity [16, 17]. These are typically used to classify movement, position, and gesture of prosthesis to varying degrees of success [18, 19]. This work examines using a CNN architecture to establish a relationship between the dissipation of vibrations in the surrounding tissue from the stimuli and the perception of textures of sandpaper. This is towards the aim of developing an autonomous system that can maintain a consistent perception of vibration, irrespective of the changes in physiology of the user.

II. Methodology

A. *Experimental Design and Procedure*

Design: Four participants above the age of 18 (1 male, 3 females) were selected and recruited from University College London (UCL), with approval from the UCL ethics committee (Project ID: 14679/001). All participants gave informed consent to the experimental procedure.

The main objective of the study was to investigate whether the perception of a specific texture could be classified using the dissipation patterns of vibration artifacts from EMG sensor electrodes and thus tuned against to ensure a consistent perception of texture. Participants were asked to adjust the PWM settings of vibration motors to mimic the perception of the three different textures of sandpaper placed in front of them. The three grades of sandpaper were as follows: coarse (FEPA grade P80), medium (FEPA grade P120), and fine (FEPA grade P240). The frequency and amplitude of each motor were controlled via two potentiometers and used to elicit three distinct perceptions of textures being rubbed along the surface of the skin. This corresponded to the effect of rubbing a finger along the different textures of sandpaper. Vibrations were controlled using an Arduino UNO and a L298N Motor driver. An EMG array was spaced equidistantly down the biceps belly of the dominant arm directly below the vibration source. Dissipation of the vibration artefacts were analyzed in post processing.

Setup: Participants were seated in a comfortable position facing a desk with their dominant arm resting on the surface. Two Precision Microdrive vibration motors (model: 334-401), were placed into a customized 3D printed case on a Velcro band and attached to the top of the bicep and triceps muscle bellies of the upper dominant arm, approximately 15cm from the elbow crease. Four surface EMG electrodes were placed distally from the motor along the biceps 2.5cm apart from each other. Two potentiometers were placed in front of the participants to control the pulse width modulation (PWM) parameters of each vibration motor. EMG signals were acquired using the TMSi porti7 amplifier, with a sampling frequency set to 512Hz, connected via Bluetooth to a laptop running open vibe software for data collection.

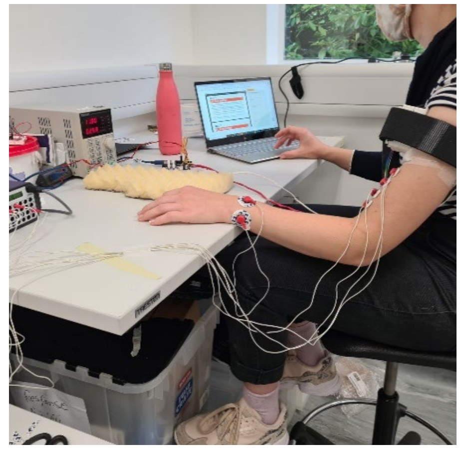

Figure I shows the experimental setup when participant is in the contracted condition

Procedure: Participants were asked to sit by an adjustable table with their dominant arm contracted and placed on the table surface. The EMG sensors and vibration motors were placed on the dominant arm of the participant, while one of three given sandpaper textures was placed in front of them. Once the experiment began, participants were required to adjust the two potentiometers until the perception of vibration matched the effect of moving their finger along the sandpaper texture. Participants were asked to make these adjustments using their non-dominant hand to prevent additional artifacts and had a five-minute time limit by which to find the appropriate settings to prevent desensitization. If participants could not find the setting in that time frame, they were allowed a 5-minute break before trying again. The chosen PWM parameters were recorded, and the task was repeated with the two other textures. Once the participants had indicated that they had matched the vibration motor parameters to all texture perceptions, they were required to stay in the seated position for 25 minutes while the vibration motor continuously ran. The vibration motors were set to run their chosen parameters for 5 minutes per texture while the EMG response was recorded. Additionally, the sensors recorded EMG data for 5 minutes while the motors were in the off state and finally, while the motor generated 5 random textures for the duration of 1 minute per texture. Participants were asked to come in on four consecutive days. The experiment was repeated over the course of the initial three days and the results analyzed in post processing at the end of the third day.

B. *Classification Methods*

Different simulations of textures are generated by varying the amplitude, frequency, and delay between each parameter of the two vibration motors. These variations can be used to classify specific perceptions of textures for each participant, using algorithms seen in multiclass classification problems. In these problems, multilayer perceptions (MLP) are used to predict outputs. In a fully connected layer, every neuron is connected to every neuron in the following layer with weights and biases to determine the best linear combination that gives the desired output. Backpropagation is used to repeatedly adjust the weights and biases while hidden layers are used to learn more complex features. In this work, two fully connected hidden layers are used after the CNN layer to classify the input.

Previous work has explored similar architectures using Long-Short Term Memory Networks and Recurrent Neural Networks in place of the CNN layer and found there to be little difference in the classification accuracy in each condition. Simple neural networks and other classifiers such as support vector machines (SVM) and K-Nearest Neighbors (KNN) produced low accuracy classifications. Overall, CNN networks tended to provide slightly higher results consistently in all conditions tested.

III. Proposed Algorithm

A. Data Segmentation

Figure II presents an overview of the algorithm applied to the collected data. The collected data is segmented into sections of 1 second. Additionally, an overlap window of 200ms is established. Other overlap window lengths of 500ms and 1s were tried but the best results were obtained with smaller window lengths. This mostly is due to most neural networks requiring larger amounts of data and the 200ms window length provides enough data.

B. Feature Extraction

Vibration artifacts can be clearly seen in the frequency domain of the EMG signal. This makes it appropriate as a means of establishing a dissipation trend across all electrodes for classification. There are many analysis techniques that were used to identify the magnitude of vibration artifacts in the EMG signal, such as pwelch, wavelet, and empirical mode decomposition analysis; however short-time Fourier transforms (STFT) were used as they provided a more consistent and richer array of information [15]. Spectrograms have the capability of retaining both time and frequency information, and so each segment of data was run through a STFT algorithm and compared against the other signals to establish the change in magnitude of vibration artifacts along the dominant upper arm. A Hamming window was also applied to reduce the possibility of spectrum leakage.

C. Classifier Architecture

Data from the three experimental days were collected and concatenated into a large, labelled dataset for each participant. The input was comprised of four sequences from the EMG recordings of the different bicep electrodes and produced one output based on the three possible sandpaper texture categories, as described above or a fourth output of undetermined. The data for each channel was concatenated into one layer and then fed into a one-dimensional CNN layer with a rectified linear activation function. Gaussian noise was added to each EMG signal input prior to concatenation as well as a dropout layer of 15% after the convolutional layer.

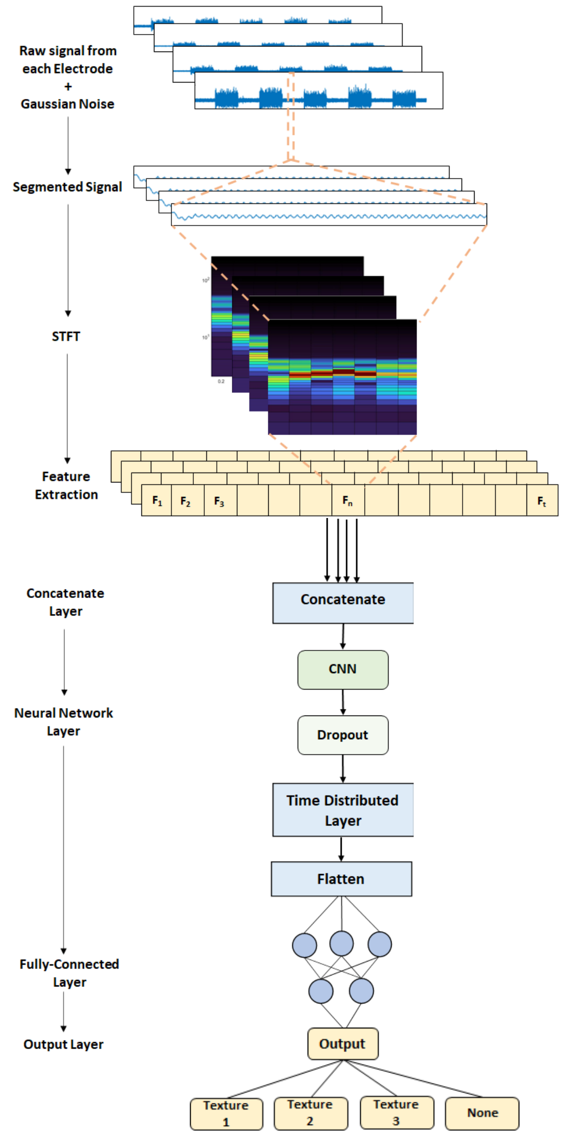

Figure II: Figure showing full architecture of classification algorithm

Following this, the data was passed through a time distributed layer, 2 fully connected layers and, finally, a softmax activation layer to give the final classification. The full architecture is given in figure II.

IV. Data Collection

On the fourth day, participants were placed in an identical experimental setup to the previous days. Seven parameter values were randomly selected from the list of nine possible parameters that participants had identified as the correct texture response over the course of the three previous days. These values were used to generate a perception of sandpaper texture. Participants were given two minutes, for each response, to verbally identify which grade of sandpaper was being induced by the motors based on four options. Their options were texture 1, texture 2, texture 3, or none of the above and corresponded to the three textures given to them

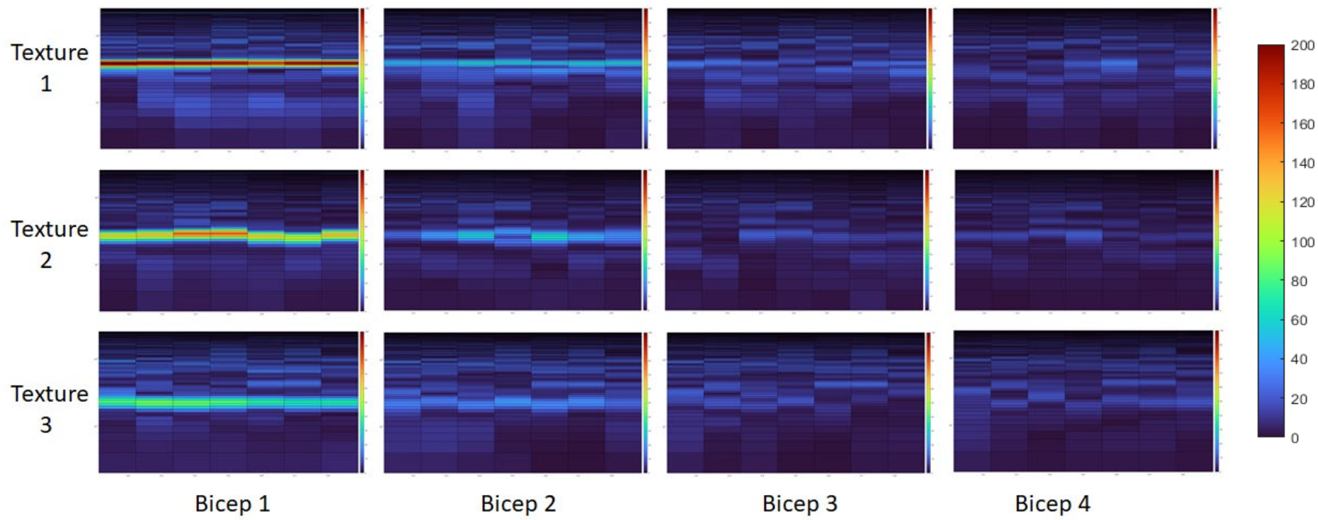

Figure III shows the log-scale spectrogram of the one second of EMG data across the four electrodes for one participant on the same day. Each row shows a specific texture pattern based on the vibration parameters the participant chose. Vibration artifacts can be clearly seen in the spectrogram as well as its decay across the electrodes. The pattern of behavior of the artifacts for each texture is different and clearly distinguishable.

on the three training days. A 2-minute break was given between every other texture to prevent desensitization. Participants also had the option of asking for texture to be repeated or to change their answers throughout the experiment. Once all textures had been identified, a five-minute break was given before moving onto the second phase of the experiment.

In the second phase of the experiment, the experimenter ran the output of the EMG signals through the generated AI base classification model. The model took real time data from the four EMG electrodes and predicted what the user might perceive the texture to be based on the associated dissipation of vibration artifacts found in the signal. The experimenter could adjust the parameters of the vibration motors, via potentiometers, until the algorithm indicated that the desired texture was achieved. A randomly generated list of seven desired textures was produced from the four options mentioned in the first phase. Participants were asked to verbally determine which texture was being presented to them and their answers noted down by the experimenter.

V. Results and Discussion

A. Model Parameter Optimization

The data collected for each participant was concatenated, labelled, randomized, and split into an 80:20 ratio, where 80% of the data was used to train the model and 20% to test. Each participant had a separately trained model associated to them, as in previous studies we found that dissipation trends of vibration artefacts were unique to individuals and remained relatively consistent over time [15]. A batch size of 32 and other associated hyper-parameters were kept constant for each participant and their corresponding model.

1) An Adams optimizer was used and trained on several different learning rates ranging from 0.1 to 1e-7. Accuracy and loss curves for all participants were generated and indicated that a learning rate of 0.001 produced the best results.

2) Overall, there were 5 distinct layers in the model. The input layer was determined by the number of EMG channels and its features were concatenated together into a single layer. A single CNN layer with a filter size of 16, padding and a kernal size of three followed by a rectified linear activation function. After the dropout layer, the data was passed into two dense layers with 8 and 4 units respectively. Finally, an output layer with 4 units corresponding to the 4 categories of classification was established and trained with the Adams optimizer mentioned above.

B. Statistical Analysis

Figure III shows the normalized power spectrum of one second of data from a participant in three different textures for one participant on day 1. The intensity of the vibration artifacts is clearly seen in all texture conditions and produces distinct patterns of behavior. The intensity of decay varies slightly in different texture conditions but is indistinguishable by the time it arrives at electrode 4, the furthest electrode from the source.

Figure IV shows a graph of correct texture identification responses per participant in both conditions. The chart in blue shows the percentage of correct responses given when previous chosen vibration parameters are used to elicit textures. The data shown in red displays the percentage of correct texture responses when the vibrations are controlled via the dissipation trends and adjusted using the machine learning classifier. The results show that, overall, participants performed better at identifying the different textures in the condition in which the machine learning classifier was used. An average texture identification score of 67.8% (18.6% STD) across all participants was achieved. This is in comparison to the condition in which the vibration

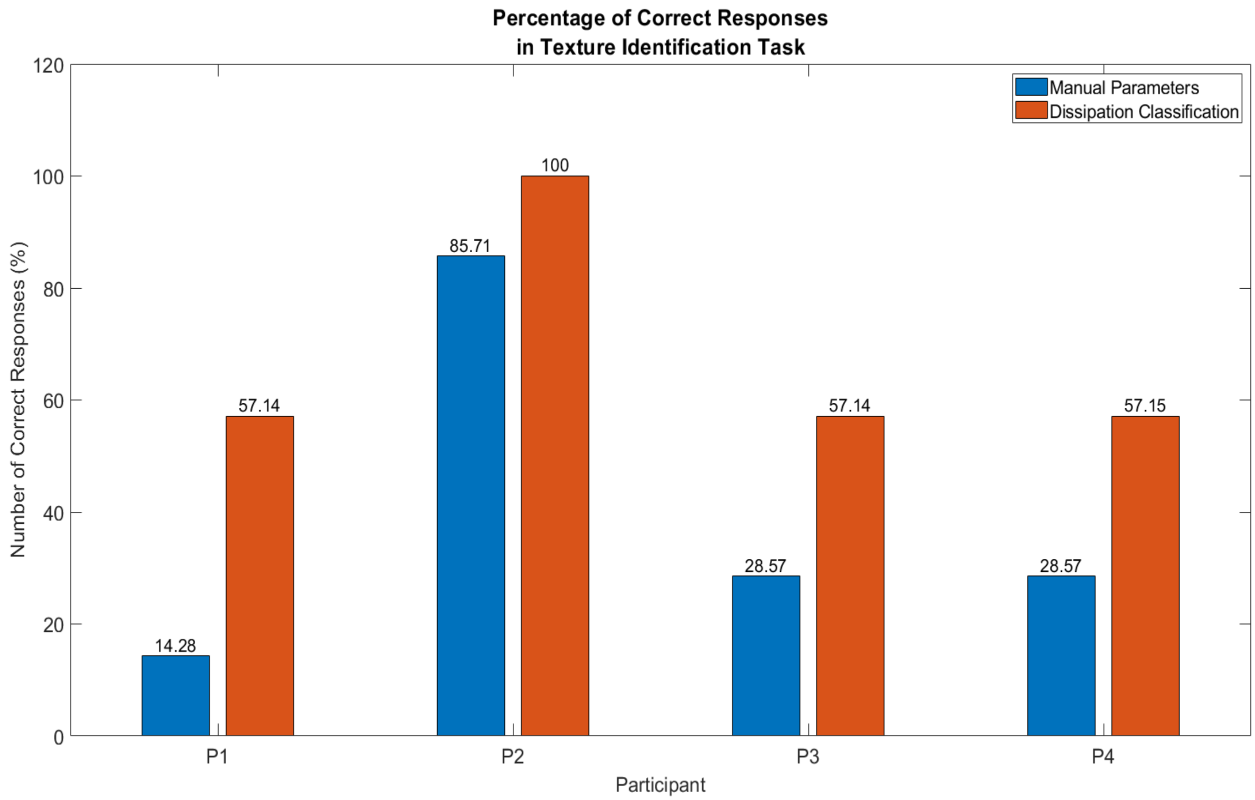

Figure IV shows a comparison of the percentage of correct responses to the texture identification task for each participant in each condition. The figure shows that participants overall performed better when using the machine learning based method.

parameters were pre-selected where an average score of 39.3% (24.4% STD) was achieved. Participants 1, 3, and 4 show increases in over 50% in accuracy when comparing the two conditions. Participant 2 scored very highly in both conditions, although still performed slightly better in the machine learning condition. Participant 2 has a history of performing texture identification tasks which may explain the discrepancy in results.

A binomial proportion confidence interval test was used to calculate the probability of success in standard Bernoulli trials. This statistical test is appropriate for this study as it shows the portion of participants who showed improvement using the machine learning method. The data shows a lower 95% confidence interval of 51.01% and an upper confidence interval of 100%. This indicated that if the experiment was repeated, 95% of the time the results would show a 51-100% improvement in the correct texture identification scores using the machine learning methodology.

Perception is highly subjective and difficult to quantify. Despite consistent vibration parameters used to elicit specific textures, these parameters do not yield the same perception of texture for the individual the following day. Even when asked to tune the parameters themselves, the values differ greatly daily. This is consistent with the results shown in this experiment as most participants only managed to identify one or two textures, despite using the parameters they had chosen. It is therefore beneficial to look at the relationship between how vibrations behave on surrounding skin tissue and how they are perceived. This experiment represents an initial exploration into a means of quantifying how users perceive modalities like vibrations by correlating it to the propagation behavior in the tissue surrounding the stimuli. Despite the small number of participants, the results obtained are promising and can be further developed into a ubiquitous method of categorizing and controlling feedback to maintain perception of texture.

VI. CONCLUSION

In this paper, we proposed an algorithm based on deep learning techniques that can classify the vibration dissipation in the dominant arm of 4 healthy participants using EMG artifacts. The EMG signals were transformed into the frequency-time domain using STFT and the data from each electrode fed into an input of the classification algorithm. Participants were asked to perform a texture identification task to compare the efficacy of tuning vibration parameters using the classification algorithm to previously determined values. This is with the aim of maintaining perception of texture over time. The results show that overall participants perform better at identifying texture when using the machine learning algorithm to classify the dissipation.

Based on these findings, we suggest that EMG artifacts can be used to categorize vibrational sensory feedback in prosthetics. This process requires no added hardware to existing myoelectric prosthesis and can, we hypothesise, be used to provide a basis for autonomous feedback in sensory feedback for prosthesis. Current work looks at improving the robustness of the AI-classifier as well as further exploring automating this process using reinforcement learning algorithms to provide consistent feedback irrespective of participant or muscle state. This will be the subject of future studies.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

VII. References

[1] P. Svensson, U. Wijk, A. Björkman, and C. Antfolk, "A review of invasive and non-invasive sensory feedback in upper limb prostheses," *Expert Rev. Med. Devices*, vol. 14, no. 6, pp. 439–447, 2017, doi: 10.1080/17434440.2017.1332989.

[2] M. D'Alonzo, F. Clemente, and C. Cipriani, "Vibrotactile stimulation promotes embodiment of an Alien hand in amputees with phantom sensations," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 3, pp. 450–457, 2015, doi: 10.1109/TNSRE.2014.2337952.

[3] T. Rosenbaum-Chou, W. Daly, R. Austin, P. Chaubey, and D. A. Boone, "Development and real world use of a vibratory haptic feedback system for upper-limb prosthetic users," *J. Prosthetics Orthot.*, vol. 28, no. 4, pp. 136–144, 2016, doi: 10.1097/JPO.0000000000000107.

[4] G. Rognini, R. Patient, M. Prosthesis, and D. By, "Multisensory bionic limb to achieve prosthesis embodiment and reduce distorted phantom limb perceptions," *J. Neurol. Neurosurg. Psychiatry*, vol. 90, no. 7, pp. 833–836, 2018.

[5] A. M. De Nunzio *et al.*, "Relieving Phantom Limb Pain with Multimodal Sensory-Motor Training.," *J. Neural Eng.*, 2018, doi: https://dx.doi.org/10.1088/1741-2552/aae271.

[6] C. Dietrich *et al.*, "Sensory feedback prosthesis reduces phantom limb pain: Proof of a principle," *Neurosci. Lett.*, vol. 507, no. 2, pp. 97–100, 2012, doi: 10.1016/j.neulet.2011.10.068.

[7] R. B. Hellman, E. Chang, J. Tanner, S. I. Helms Tillery, and V. J. Santos, "A Robot Hand Testbed Designed for Enhancing Embodiment and Functional Neurorehabilitation of Body Schema in Subjects with Upper Limb Impairment or Loss," *Front. Hum. Neurosci.*, vol. 9, no. February, pp. 1–10, 2015, doi: 10.3389/fnhum.2015.00026.

[8] F. Clemente, M. D'Alonzo, M. Controzzi, B. B. Edin, and C. Cipriani, "Non-Invasive, Temporally Discrete Feedback of Object Contact and Release Improves Grasp Control of Closed-Loop Myoelectric Transradial Prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2016, doi: 10.1109/TNSRE.2015.2500586.

[9] B. Peerdeman *et al.*, "Myoelectric forearm prostheses: State of the art from a user-centered perspective," *J. Rehabil. Res. Dev.*, vol. 48, no. 6, p. 719, 2011, doi: 10.1682/JRRD.2010.08.0161.

[10] F. Cordella *et al.*, "Literature review on needs of upper limb prosthesis users," *Front. Neurosci.*, vol. 10, no. MAY, pp. 1–14, 2016, doi: 10.3389/fnins.2016.00209.

[11] S. Huang and H. Wu, "Texture recognition based on perception data from a bionic tactile sensor," *Sensors*, vol. 21, no. 15, 2021, doi: 10.3390/s21155224.

[12] B. Stephens-fripp, B. Stephens-fripp, R. Mutlu, and G. Alici, "Using Vibration Motors to Create Tactile Apparent Movement for Transradial Using Vibration Motors to Create Tactile Apparent Movement for Transradial Prosthetic Sensory Feedback," no. August, 2018.

[13] B. Stephens-Fripp, G. Alici, and R. Mutlu, "A Review of Non-Invasive Sensory Feedback Methods for Transradial Prosthetic Hands," *IEEE Access*, vol. 3536, no. c, pp. 1–1, 2018, doi: 10.1109/ACCESS.2018.2791583.

[14] D. A. Mahns, N. M. Perkins, V. Sahai, L. Robinson, and M. J. Rowe, "Vibrotactile Frequency Discrimination in Human Hairy Skin," *J. Neurophysiol.*, vol. 95, pp. 1442–1450, 2006, doi: 10.1152/jn.00483.2005.

[15] M. Magbagbeola, T. J. Vojinovic, M. Miodownik, S. Hailes, and R. C. V. Loureiro, "An Investigation into the Dissipation of Vibrations Using Electromyography towards the Development of Self-Adapting Robotic Prosthesis," *Proc. IEEE RAS EMBS Int. Conf. Biomed. Robot. Biomechatronics*, vol. 2020-Novem, pp. 740–745, 2020, doi: 10.1109/BioRob49111.2020.9224402.

[16] D. Huang and B. Chen, "Surface EMG Decoding for Hand Gestures Based on Spectrogram and CNN-LSTM," *Proc. - 2nd China Symp. Cogn. Comput. Hybrid Intell. CCHI 2019*, vol. 1, pp. 123–126, 2019, doi: 10.1109/CCHI.2019.8901936.

[17] X. Zhai, B. Jelfs, R. H. M. Chan, and C. Tin, "Self-recalibrating surface EMG pattern recognition for neuroprosthesis control based on convolutional neural network," *Front. Neurosci.*, vol. 11, no. JUL, pp. 1–11, 2017, doi: 10.3389/fnins.2017.00379.

[18] N. Parajuli *et al.*, "Real-time EMG based pattern recognition control for hand prostheses: A review on existing methods, challenges and future implementation," *Sensors (Switzerland)*, vol. 19, no. 20, 2019, doi: 10.3390/s19204596.

[19] D. Farina *et al.*, "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 797–809, 2014, doi: 10.1109/TNSRE.2014.2305111.