Correlating Vibration Patterns to Perception of Tactile Information for Long-Term Prosthetic Limb Use and Continued Rehabilitation of Neuropathic Pain

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Abstract— **Prosthetic limbs (and orthotic devices) have been used as a paradigm for the treatment and rehabilitation of neuropathic pain, such as phantom limb pain. Long-term adoption of the devices for the continued use in rehabilitation remains low in part due to reduced embodiment and the high cognitive load associated with controlling the device. Previous research has shown that incorporating sensory feedback in prostheses can provide proprioceptive information, increase control and manipulation of objects, and improve embodiment. However, feedback experienced by the user varies daily and requires constant parameter adjustments to maintain accurate and intuitive sensory perception, further preventing long term adoption. Work therefore needs to be explored that correlate feedback modalities to perception of tactile information, such as texture and pressure. The work presented in this paper begins to explore this by utilizing a deep-learning algorithm to classify the dissipation of vibration artefacts found in the EMG signals of able-bodied individuals to specific texture patterns. Four texture patterns were applied to 7 participants using two vibration motors and repeated 3 times. In post processing, a RNN network identified the artefact features along equidistantly spaced EMG electrodes and correctly classified unseen data from each participant.**

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

I. Introduction

Prosthetic limbs have been used in research as a rehabilitation paradigm in the treatment of neuropathic pain. It was found that long term, continued use of a hand prosthesis, as well as effective embodiment of the device, can lead to a reduction in neuropathic pain, for example, phantom limb pain [1]. Considerable work has been reported in the literature to improve embodiment and long-term adoption of prosthetic hand via the enhancement of effective sensory feedback from the device [1-5]. Somatotopically mapped feedback is often used in hand prostheses to provide information on grasping, texture, and the shape of objects [6]. The most common type of sensory feedback is vibration, as its versatility can elicit a wide range of proprioceptive information that can be applied to any surface on the users' body and mapped to the appropriate function or feedback [6-8]. Despite success in robotic prosthesis control and discernable sensory feedback, vibrations and other modalities are often not utilized in a hand prosthesis, due in part to the variation of the resulting perceptions for the user [9, 10]. For example, perceptions of texture generated by vibrations would feel different to the user on a different day despite the consistency of the parameter settings and the device used. Additionally, the same parameters may not provide the same perception of texture for a different user. This results in the requirement of daily fine-tuned parameter adjustments to maintain accurate and intuitive feedback from the device. It is believed that individual differences and changes in the physical attributes of the users are the cause of these changes in the perception of the feedback, and thus, prevents a ubiquitous system or setting that will maintain accurate long-term feedback [9, 11]. Consequently, this prevents long term adoption of sensory feedback in prosthetic limbs. Peerdman et al found that easy, intuitive, and adjustable feedback was amongst the priorities for individuals with non-invasive prosthesis uses [12].

Despite research showing an increase in control and embodiment with sensory feedback, more focus has been placed on motion control of prosthetic limbs using surface electromyography (sEMG). Combinations of pattern recognition algorithms, dimensionality reductions, and feature extractions have become well-known techniques in upper limb prosthetic control. These combinations have been found to help with motion control, grasping, and gesture classification for upper limb prosthesis [2]. Time and frequency domain features of muscle activity are often used for movement, position, and gesture classification of hand prostheses to varying degrees of success [13, 14]. In an analogous way to sensory feedback, individual differences,

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along with sensor placement and electrical noise, affect the quality of the signal recorded. Modern techniques in machine learning and deep learning, such as recurrent neural network (RNN) or, in some cases, convolutional neural network (CNN) algorithms, have shown promising results in feature extraction and sequence classification of these types of signals [15, 16].

Though pattern classification techniques have been explored greatly in the field of movement and grasping control in hand prostheses, they have not been explored as much in the context of sensory feedback and its resulting perceptions. This work examines the classification of texture perceptions induced by vibration motors on the dominant upper arm of the participants using sEMG with an RNN-based architecture. Previous work has found that vibrations produce distinct artefacts in the frequency spectrum of sEMG signals. These artefacts are distinct enough in the frequency domain to detect subtle differences between individuals. Thus, a unique dissipation trend based on the magnitude of the artefact at each electrode along the biceps can be produced [17]. These dissipation trends are unique to individuals and do not vary greatly over time; they can therefore be used to categorize and adjust sensory feedback by correlating the trend to specific subjective tactile experiences. This can form the basis of a system that can maintain a consistent perception of vibration irrespective of physiological differences for long term upper limb prosthesis use.

II. METHODS

A. *Experimental Design and Procedure*

Design: Seven participants above the age of 18 (4 females, 3 males) 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 if different texture perceptions could be classified using the dissipation patterns of vibration artifacts from EMG sensor electrodes. This was done by varying frequency and amplitude between two motors located on the dominant upper biceps and triceps of each participant. Different combinations of frequencies between the two motors elicited 4 distinct texture effects. This was repeated at three different voltages to vary the amplitude. 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. Participants were asked to hold a known weight and contract or relax their arm every 30 seconds. Dissipation of the vibration artefacts were analyzed in post processing.

Setup: Participants stood facing a computer screen placed on an adjustable desk. While standing in the relaxed position, their dominant hand was resting parallel to their body by their side. In the contracted condition, participants were asked to lift a known weight of 1023g in their hand until the elbow joint was flexed at 90 degrees, as shown in figure I. While the elbow was flexed, the adjustable desk was raised until the participants' hand, in supination, was touching the underside of the desk. This, in addition to lifting a known weight, ensured that participants would maintain the same level of contraction throughout the experiment. The computer screen displayed a simple graphical user interface to instruct the participant to contract or relax their biceps at the correct timing intervals.

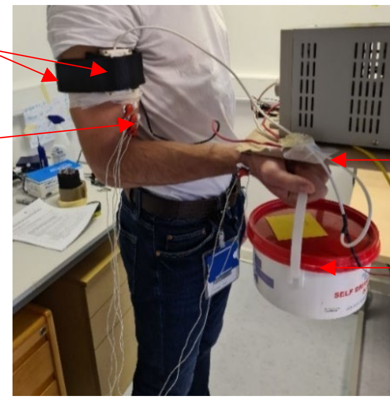

Figure I shows the experimental setup when participant is in the contracted condition

Two Precision Mircodrive vibration motors (model: 334-401), were placed into a customized 3D printed case on a Velcro band and attached to the top of the biceps 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. EMG signals were acquired using TMSi porti7 amplifier, with a sampling frequency set to 512Hz, connected via Bluetooth to a laptop running open vibe software for data collection.

Procedure: Participants were asked to face the computer, holding the weight by their side with the EMG sensors and vibration motors correctly placed. Once the experiment began, the initial muscle state was a relaxed position, in which participants were required to hold the weight to their side for 30 seconds. Following this, participants contracted the bicep by lifting the weight to the underside of the desk, holding this position for 30 seconds. This cycle repeated for the duration of the experiment while different texture patterns were applied via the vibration motors. This procedure was repeated three times with a ten-minute break between the sessions. It was repeated at 3 different voltages in the range 8 – 11V. At a max PWM of 255 at 8, 9, 10, 11V, the vibration motor oscillated at approximately 50, 58, 64 and 71.5Hz respectively.

B. *Classification Methods*

Elicitation of different textures with vibration motors was achieved by varying the amplitude, the frequency, and the delay between the two parameters. Due to this, one full textural response occurs when the PWM signal steps through all values between the high and low parameter outlined in table I. Within that cycle the dissipation trends will correspondingly change along with the frequency and amplitude repeating as the cycle restarts.

Vibration Condition	PWM	Biceps Electrodes	
		Relaxation	Contraction
Texture 1	High: 160 Low: 45	R1	C1
Texture 2	High: 180 Low: 100	R2	C2
No Vibration	-	R3	C3
Texture 3	High: 190 Low: 70	R4	C4
Texture 4	High: 150 Low: 60	R5	C5

TABLE I: Conditions of the study. Each PWM would rise by a step of 20 starting from the low value until the high condition was reached. This cycle was repeated for the duration of the condition.

This means that a single dissipation trend is not enough to classify the signal but, instead, the dissipation at each electrode and how it changes during one full cycle is required.

Standard classification methods such as SVM and KNN are not sufficient for this type of problem and, when tested against the data in this study, could not produce accuracy of above 20%. This is potentially due to requiring each vibration dissipation state to be known within a full cycle to make a prediction. Therefore, some memory is needed in the classification process to keep track of the data that has already occurred. For data that is time-dependent, like EMG waveforms, recurrent neural networks (RNN) are appropriate to use as they can make predictions based on recent information. This is suitable for our work since some past data is needed to make accurate predictions for texture classification. However, if the relevant information is too far back from the current state, the efficacy of RNNs decreases. The long short-term memory (LSTM) network is a variation of RNNs and can be used to classify data when the relevant information needs to be remembered over a period of time and so can deal with long-term dependent data [18, 19]. They are often used in time series prediction.

A RNN node has a single weight and bias that loops round to act like a successive chain of nodes. By contrast, a LSTM network contains three gated layers that controls the information added or removed from the cell to allow long term dependencies to be captured. The three gates are the forget gate, input gate and output gate. The forget gate controls which data from the previous step is needed and the input gate controls which information from the current step is important. The output gate determines the value of the next hidden state and contains the information of previous inputs. In multiclass classification 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 LSTM layer to classify the input.

III. Proposed Algorithm

A. Data Segmentation

Figure II presents an overview of the algorithm applied to the collected data. Once the data is initially collected, it is segmented into sections of 1 second as the motors elicit one full cycle of the textural perception within that time frame. This is based on the rising time of each motor in the experimental set-up and allows for at least 3 complete rotations of each motor for each step in one cycle of the textural perception. 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 overlap window length providing enough data.

B. Feature Extraction

In this study, peaks of the vibration artifacts are clearly seen within the frequency domain and this is used to establish a dissipation trend for classification. Spectrograms are an efficient and convenient method of retaining both time and frequency information and so each segment of data is run through a Short-Time Fourier Transform (STFT) algorithm to establish the magnitude of the vibration artifact. In addition, the values in the spectrogram are normalized to the largest peak value. As shown in previous studies, other analysis techniques such as pwelch or wavelet analysis show the presence of vibration artifacts [17]; however, the Fast Fourier analysis provided the most consistent results when applied to dissipation trends. A Hamming window was applied to reduce the possibility of spectrum leakage.

C. Classifier Architecture

Our input is comprised of four sequences from the EMG recordings of the different bicep electrodes and produces one output based on the 10 possible categories shown in table I. The data for each channel was then fed into either a simple RNN or a Long Short-Term Memory (LSTM) layer with a sigmoid activation function and the outputs were concatenated into one layer. Following this, the data was passed through 2 fully connected layers and, finally, a softmax activation layer to give the final classification. The full architecture is given in Figure II.

IV. Results

A. Evaluation Metrics

We evaluate the classification performance using two metrics: accuracy and loss. Accuracy is defined as:

$$Accuracy\ (\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

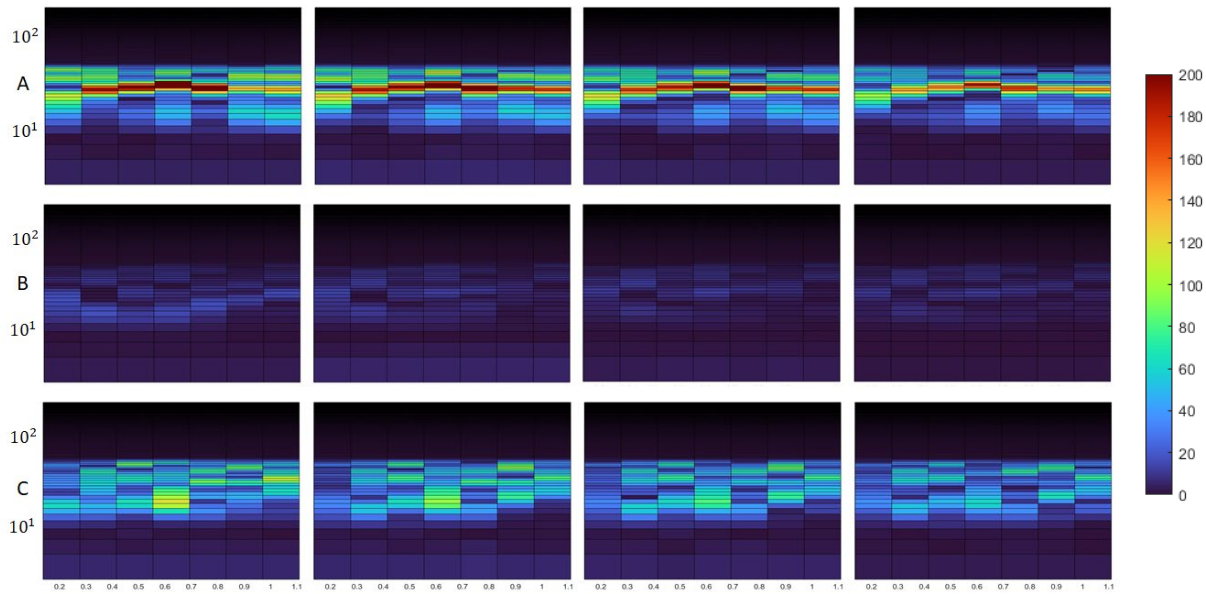

Figure III shows the log-scale spectrogram of the one second of EMG data across the four electrodes. Row A is taken when the participant is in the contracted condition for texture 1 while row B shows the relaxed condition for the same texture. Row C shows the contracted condition without any vibration. The raw values of these spectrograms were fed into the LSTM algorithm.

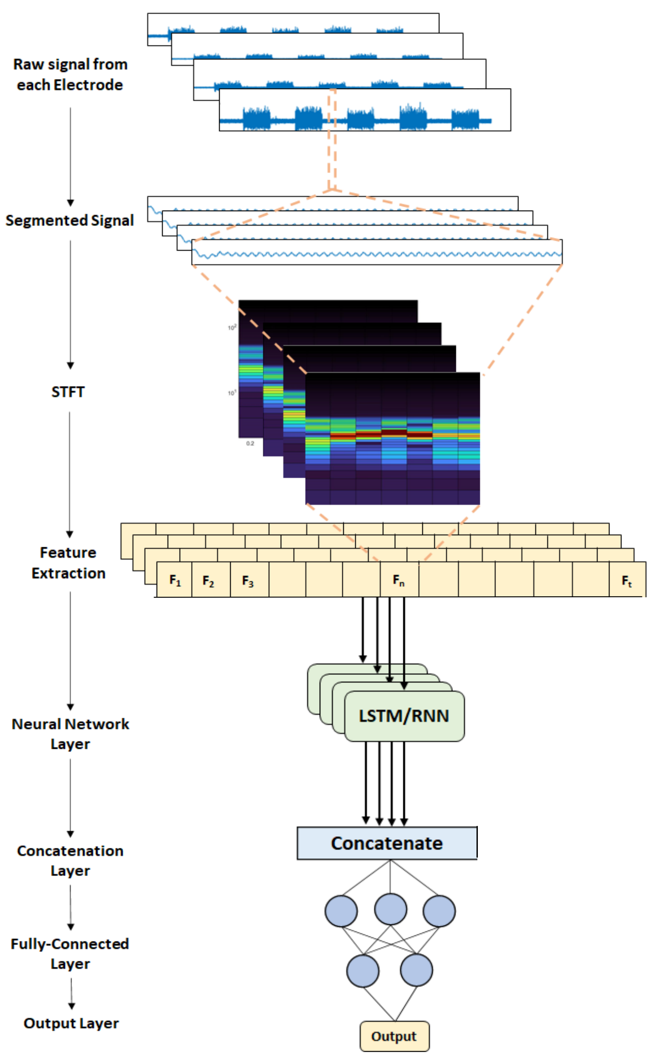

Figure II: Figure showing full architecture of classification algorithm

Where TP, TN, FP, and FN are true positive, true negative, false positive and false negative respectively. Loss is defined as the difference between the predicted and true value of the model. In this study, we used categorical cross entropy loss due to the categorical nature of the outputs. Typically, loss and validation curves can inform us whether the model is over or underfit.

B. *Model Parameter Optimization*

The dataset for each participant was split to a ratio of 80:20, where 80% of the data was used to train the model and 20% to test. This is a standard ratio used in training machine learning models. The model was trained separately for each participant as, in previous studies, we found that whilst dissipation trends were unique to each participant, they remained same for each individual over multiple days [16]. The normal hyper-parameters found in the network described remained the same for each model trained. The batch size for all participants in all conditions was kept constant at a size of 32.

1) An Adams optimizer was used and trained on several different learning rates ranging from 0.1 to 1e-7. It was found that, for all participants, 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 passed into an LSTM or an RNN layer composed of 32 units. This was followed by a sigmoid activation function. After the concatenation layer, the data was passed into two dense layers with 64 and 32 units respectively. Finally, an output layer with 10 units corresponding to the 10 categories of classification was established and trained with the Adams optimizer mentioned above.

Figure III shows the normalized power spectrum of one second of data from a participant in three different conditions. The intensity of the vibration artifacts is clearly seen in both figures A and B as well as how they change over the course of 1 second, the time taken to complete one cycle of texture perception. No discernable pattern is seen in figure C as no distinct peaks nor pattern of behavior can be seen over the course of one second. The results from the experiments show that while accurate classification is possible with this architecture, there is no added benefit in using a LSTM based design over an RNN. This suggests that while the data is temporally related and requires some degree of memory, recent data alone is sufficient. This can be seen in the classification accuracy results in figure V. The accuracy in all conditions ranges between 75-100% in both LSTM and RNN architectures. Using an RNN over LSTM can be advantageous as it requires fewer computations and fewer parameters to achieve similar results. This could be beneficial for future studies, as reduction in computational costs makes translation to hardware easier.

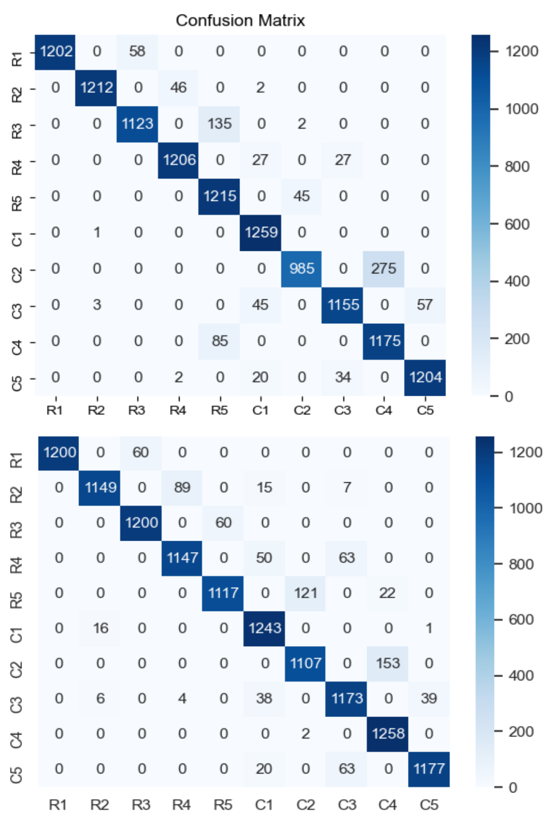

Figure IV shows the confusion matrix for all participants for both LSTM (top) and RNN (bottom) architectures.

Figure IV shows the confusion matrix for all participants and that the proposed algorithm can distinguish between the different conditions efficiently. Though all participants are concatenated into a single confusion matrix, closer analysis shows that the biggest source of false positives was in the identification of C2 as C4 for multiple participants for both LSTM and RNN architectures. The RNN architecture also had trouble distinguishing between R3 and R5 while the LSTM model often classified R5 as C2. As the PWM range

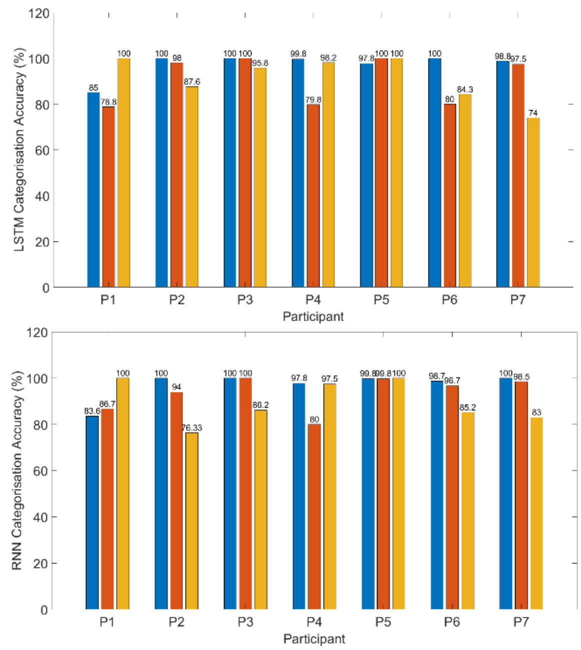

Figure V shows the classification accuracy of the model for all participants in three different voltage conditions. For participants 1 – 5, the voltages are 8v (blue), 9v(orange) and 10v(yellow) for participants 6 and 7 the voltages are 9,10,11v respectively.

is relatively similar between the different conditions, shown in table I, this could explain why same false positives are seen in multiple participants across the two models. Future experiments will explore a wider range of textural perceptions on more participants to determine any limitations in the algorithm. While both architectures show the same patterns of false positives, they still show a high degree of accurate classifications.

V. Discussion and Conclusion

In this paper, we proposed an algorithm based on deep learning techniques that can classify the vibration dissipation in the dominant arm of 7 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. The results show a high degree of classification accuracy using this technique, with some results reaching 100% classification accuracy.

How the user perceives sensory information is important for the rehabilitation process and the long-term hand prosthesis use as it might improve the control and embodiment of the device. However, perception of the sensory information often changes daily for users due to physiological differences and results in constant fine-tuning of the feedback parameters, preventing long term adoption. It is therefore important to understand the relationship between vibrational feedback and how it is perceived. This will allow a method to be devised that considers these differences and modulates the feedback accordingly to maintain perception.

The results from previous studies suggest that patterns of vibration dissipation are unique to individuals [16] whilst the results presented in this paper show that oscillating vibration patterns, often used to relay proprioceptive information to

Upper limb prosthetic users or provide discernable feedback such as texture, can be categorized using AI-based classification methods. This is beneficial to the field as correlating dissipation patterns to perceptions of tactile information, such as texture and pressure, can provide a mechanism for maintaining consistent, intuitive feedback. This is turn allows for long-term prosthesis use for the continued treatment and rehabilitation of neuropathic pain. Future work aims to provide a ubiquitous, autonomous method for tuning vibration parameters based on dissipation trends, with the aim of maintaining the perception of textures over time.

Conflicts of Interest

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

VI. References

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