BE005

LOW-COST 3D-PRINTED PROSTHETIC HAND

Abstract

Current prosthetic hands are extremely expensive and thus inaccessible to patients with upper limb deficiency in impoverished countries. Hence, we wish to 3D-print a low-cost prosthetic hand. Analysis of electromyography (EMG) signals with the bandpass filter and fast fourier transform (FFT) yielded characteristic frequencies and amplitudes unique to certain motions, identifying motions with a 10% total error rate, thus this method is suitable for identification of patients' desired motions and control of the hand. Furthermore, the system allows for quick patient training and adaptation for a fairly accurate identification of motion. A novel electrically conductive acrylonitrile butadiene styrene/carbon nanotube (ABS/CNT) composite can be 3D-printed with the hand, allowing it to interface with touchscreens. Testing of ABS/CNT strips with different surface areas on an capacitive touchscreen revealed a direct linear correlation between the effectiveness of the finger-touchscreen interface and the surface area of ABS/CNT used. Experiments with the finger on a capacitive touchscreen at different velocities revealed a inverse linear relationship between the velocity of the finger and the effectiveness of the finger-touchscreen interface. Overall, a proof of concept of a digit capable of interacting with a touchscreen has been demonstrated and shows the feasibility of such an endeavour.

Research Plan

(a) Rationale

Upper limb deficiency is highly prevalent worldwide, with the World Health Organisation estimating that 30 million people worldwide require prosthetic limbs. However, fewer than 20% of patients receive a prosthetic. Due to the prohibitive cost of more advanced prosthetics, many patients cannot afford their treatment, while the extremely limited functionality of cheaper models results in high rejection rates. Hence, we propose a novel 3D-printed hand with a electrically-conductive ABS/CNT composite that can be 3D-printed with the hand, which enables interfacing with touchscreens, an important ability in modern living.

(b) Research Question(s), Hypothesis(es), Engineering goal(s) and Expected Outcome(s)

We aim to use the 8-channel Myo armband to measure electromyography (EMG) signals from specific muscle groups and correlate with different hand movements including swiping. We also aim to use the acrylonitrile butadiene styrene/carbon nanotube (ABS/CNT) composite to enable interfacing with capacitive touchscreens.

(c) Procedures, Risk and Safety and Methods for Data Analysis

Procedure for EMG Signal Processing: Capture 10 sets of EMG data each for the precision grip (pinch), power grip (clench) and vertical swiping motions from the Myo armband using the Myo Data Capture application from a test subject. Process and analyse the EMG data then using the bandpass filter and fast fourier transform (FFT) implemented in Mathematica 11.

Procedure for tests on capacitive touchscreen interface: Attach a 3D-printed finger with the tip pointing down to a conveyor belt controlled by the Lego Mindstorms EV3 system. Place a touchscreen directly below the finger. Swiping motions can be performed on the touchscreen with a constant pressure and velocity. The velocity of the finger swipe and surface area of the ABS/CNT on the finger can then be varied as follows.

Procedure for varying velocity of finger swipe: With a piece of ABS/CNT attached to the fingertip, adjust the rotation speed of the conveyor belt to vary the velocity of the finger swipe motion. Measure the accuracy of the touchscreen-finger interface by counting the number of pixels activated and deviation from the expected straight line path.

Procedure for varying surface area of ABS/CNT: Print out 6 pieces of ABS/CNT of varying surface areas. Attach one piece to the tip of the finger, and ground the ABS/CNT by attaching a crocodile clip that is connected to ground. Measure the accuracy of the interface by counting the number of pixels activated and deviation from the expected straight line path. Repeat for the remaining pieces of ABS/CNT.

Risk and Safety: 3D printing is a potentially dangerous activity, but it is carried out by the lab staff. However, the particulate emissions produced during 3D printing could be hazardous. Hence, close the printer lid before printing and reduce contact with the 3D printer and its vicinity when it is operating.

Data Analysis: EMG data gathered was processed with the bandpass filter and fast fourier transform implemented in Mathematica 11.

(d) Bibliography from literature review

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Report

1. INTRODUCTION

Upper limb deficiency is highly prevalent worldwide, with the World Health Organisation estimating that 30 million people worldwide require prosthetic limbs. However, fewer than 20% of patients receive a prosthetic [1]. Due to the prohibitive cost of more advanced prosthetics, many patients cannot afford their treatment and turn towards cheaper models, but the extremely limited functionality of cheaper prosthetic hands results in high rejection rates. Hence, we aim to produce a prosthetic hand that is both low-cost and fairly functional to benefit more patients.

1.1 Purpose of Research

The aim of the research is to create a 3D-printed prosthetic hand that is actuated by an EMG-controlled cable system and supports interfacing with touchscreens.

2. LITERATURE REVIEW

2.1 Current Prosthetics

The most advanced prosthetics are myoelectric and have relatively many degrees-of-freedom (DOFs) in the fingers, thus they can execute the user's desired motions fairly well. However, these are prohibitively expensive, with one, the BeBionic3, costing an upwards of US$35,000, and another, the i-limb produced by Touch Bionics, costing an upwards of US$120,000 [2]. As a result, many users opt instead for lower-cost but less functional hands, but the limited functionality and the heavy weight of the hand can deter users. In addition, even purely cosmetic, nonfunctional hands can cost thousands.

Meanwhile, 3D-printing offers a lower-cost solution, with 3D-printed hands being much less expensive, more customisable and lightweight. Examples include the myoelectric Hero Arm by Open Bionics, which costs about US$7,000 and can be printed in only 40 hours [3]. As such, we wish to produce a low-cost prosthetic hand by using 3D-printing.

2.2 Capacitive Touchscreens

As technology becomes more pervasive in the world, smartphones and other touchscreen devices have become more widely used. As such, current prosthetic hands should be adapted to interface with capacitive touchscreens, the most commonly used type of touchscreen, to meet the increasing demands of prosthetic users. However, to the best of our knowledge, only the most expensive prosthetic hands (such as the i-limb) are capable of doing so, and there are no known 3D-printed hands with touchscreen capabilities.

Capacitive touchscreens can only interact with materials with a similar or greater conductivity and charge capacity as the human hand, whereas most 3D-printed prosthetic hands use thermoplastic filaments that cannot conduct electricity. Using a novel acrylonitrile butadiene styrene/carbon nanotube (ABS/CNT) composite created by Zhong, Lin, Chor and Tan [4], this limitation can be overcome by printing a network of electrically conductive ABS/CNT on the fingers, which allows the fingers to interface with capacitive touchscreens. As such, we have adopted such a design in our prosthetic hand (Fig. 1c in Appendix A).

This network of embedded conductive ABS/CNT will also serve as the basis for the control of a cable actuation system, and a future extension of a feedback system, which is crucial to patient comfort and hand functionality [5].

2.3 Metrics to Judge Prosthetics

When choosing a prosthetic hand, patients consider several crucial factors: functionality, maintenance, cost and cosmetics. Functionality is the range of motions a hand can execute, typically measured by the number of grips and DOF it has. These affect the number of instrumental activities of daily living (iADLs) that the hand can perform, such as communications, which now commonly require smartphone usage for long-distance communications. Of the hand gestures, the power grip (clench) and precision grip (pinch) are two of the largest classes of hand grasps, so it is crucial for prosthetic hands to be able to perform these grasps [6], and to interact with touchscreens, the fingers should be capable of performing swiping and tapping motions. Maintenance refers to how often the hand must be replaced due to wear and tear, which affects cost since a prosthetic is ideally replaced every 2 years for an adult and less than 6 months for a child, whose residual will change shape with growth. 3D-printed prosthetics are able to greatly reduce maintenance time and costs, increasing their attractiveness to patients. Cosmetics refers to the visual attractiveness of the prosthetic, and is usually achieved by creating a hand design that is closely approximated to an actual hand, with similar skin tone and size.

Upper limb prosthetics from Tan Tock Seng Hospital (TTSH) emphasise more on cosmetics rather than functionality, such that many are nonfunctional. To incorporate the need for cosmetics while still retaining the functionality of our prosthetic hand, a glove can be 3D-printed using skin-colored flexible filament for the hand to be inserted into.

3. METHODOLOGY

3.1 Signal Processing with the Myo Armband

Myo (Fig. 2 in Appendix B), produced by Thalmic Labs, is an armband with 8-channel EMG sensors costing USD$200. Unlike typical surface EMG sensors, such as the MyoWare Muscle Sensor, the Myo armband can be easily and conveniently worn on and removed from the arm, without having to shave or apply gel to the area prior to usage. It is simple and non-invasive, making it suitable for everyday use [7]. Myo has been used to control prosthetic hands by researchers at Johns Hopkins University to improve the Modular Prosthetic Limb [8]. A software development kit allows users to obtain the raw EMG data collected by the armband. Using the armband, EMG data of three gestures (clenching, pinching and swiping) will be recorded, filtered using a bandpass filter and processed using Fast Fourier Transform, from which the results will be used to determine the actuation of the prosthetic hand, which will be done using an Arduino Uno microcontroller.

3.2 Capacitive Touchscreen

To design an effective touchscreen-finger interface, the surface area of ABS/CNT used should be optimised. To find the optimal surface area, the surface area of the material in contact with the touchscreen was varied by printing 6 strips of ABS/CNT of varying lengths from 0.50cm to 3.00cm in intervals of 0.50cm. The width and thickness of 0.50cm and 0.20cm respectively were kept constant. The material has a volume resistivity of 30Ω cm.

By attaching the finger to the conveyor belt controlled by the Lego Mindstorms EV3 system, the finger can simulate various movements, including swiping at a constant velocity and pressure, mimicking real gestures that are used to interact with touchscreens (Fig. 3a & 3b in Appendix C).

4. RESULTS AND DISCUSSION

4.1 Signal Processing of EMG Signals

10 sets of EMG data each for the precision grip (pinch), power grip (clench) (Fig. 4a & 4b in Appendix D) and vertical swiping motions were captured from the Myo armband using the Myo Data Capture application. The precision grip and power grip motions were selected as they are highly representative of a range of hand motions that are required in iADLs, while the swiping motion simulates the motions involved in using phones. EMG data naturally contains large amounts of noise due to the uncontrollable shaking of the hand or from ambient electromagnetic radiation that could interfere with user control [9].

Due to embedded system constraints on data transmission bandwidth and power consumption, the Myo armband has a low sampling frequency of 200Hz. According to Nyquist–Shannon sampling theorem, the highest detectable frequency component is half of the sampling frequency, i.e. $f_{component} \leq \frac{1}{2} f_{sampling}$, so only EMG signals of up to 100Hz can be detected by the Myo armband [10]. However, this is still suitable for capturing significant EMG data, as most dominant EMG signals fall within the range of 50-150Hz while noise falls largely within the 0-20Hz range [11]. In our testing, characteristic frequencies largely lie within a small range of 80Hz to 95Hz; hence, to remove noise and improve the user experience, the data was passed through a bandpass filter with thresholds set at 80Hz to 95Hz in Mathematica. It is observed that the bandpass filter is able to smoothen the graph and eliminate some random fluctuations. This output is then be processed through the Fast Fourier Transform (FFT).

The FFT samples a signal over a specified period of time or data points and then divides them into distinct frequency components, which can reveal key patterns in the data. Using the Fourier function implemented in Mathematica, the data was processed, revealing characteristic frequencies for each of the motions observed across most of the EMG data sets (Fig. 5a, 5b & 5c in Appendix E). Furthermore, each type of motion also resulted in different ranges of amplitudes of the characteristic frequencies. For instance, the stronger power grip motion results in a higher range of amplitudes of its characteristic frequency than the weaker precision grip motion. Hence, given the characteristic peaks and amplitudes of the motion, the software is able to identify the motion carried out by the user.

Additionally, since the amplitudes of the EMG signals detected correlate with the strength of the motion performed by the user [12], this information can be used to control the amount of force delivered by the motors of the cable actuation system and hence give the user finer control over the strength of their grip or swipe, improving the sensitivity of the system and the user experience greatly.

10 EMG datasets were used to determine the classification accuracy of our signal processing method using the total error rate (TER). An incorrect decision is defined when an EMG for one motion is identified incorrectly as another motion. TER is then calculated using the following formula:

$$TER = n_{incorrect\ decisions} / n_{total\,decisions}$$

Equation 1: Total Error Rate

Table 1: Results for accuracy of EMG signal processing

Type of Motion	Characteristic Frequency/Hz	Amplitude/Arbitrary Units	Total Error Rate
Precision grip	90	0.3 - 0.6	10%
Power grip	82 - 83	1.1 - 1.8	
Vertical swiping	93	0.5 - 1.2	

Considering that only 10 sets of EMG data for each motion were used to identify the characteristic frequencies and amplitudes, the accuracy of the system is quite high with a TER of 10%. This suggests that using this system, patient training and adaptation for a fairly accurate identification of motion can be achieved rapidly, in contrast with other systems such as the Myo armband's inbuilt gesture recognition, which requires thousands of EMG data sets to build up a large enough database to recognise individual gestures, and even then, machine learning had to be used. The accuracy of the system is important for patient uptake of our prosthetic hand, to reduce misidentification of the patient's desired motions. Misidentification can lead to frustration, which can cause patients to give up on using the hand and result in a lower quality of life, and so should be avoided.

4.2 Capacitive Touchscreen

4.2.1 Surface Area

Simulating a swipe motion at 3.35cm s^{-1}, 6 readings were taken for each surface area of ABS/CNT (Table 2 in Appendix F). The average reading was then calculated and graphed to give the following:

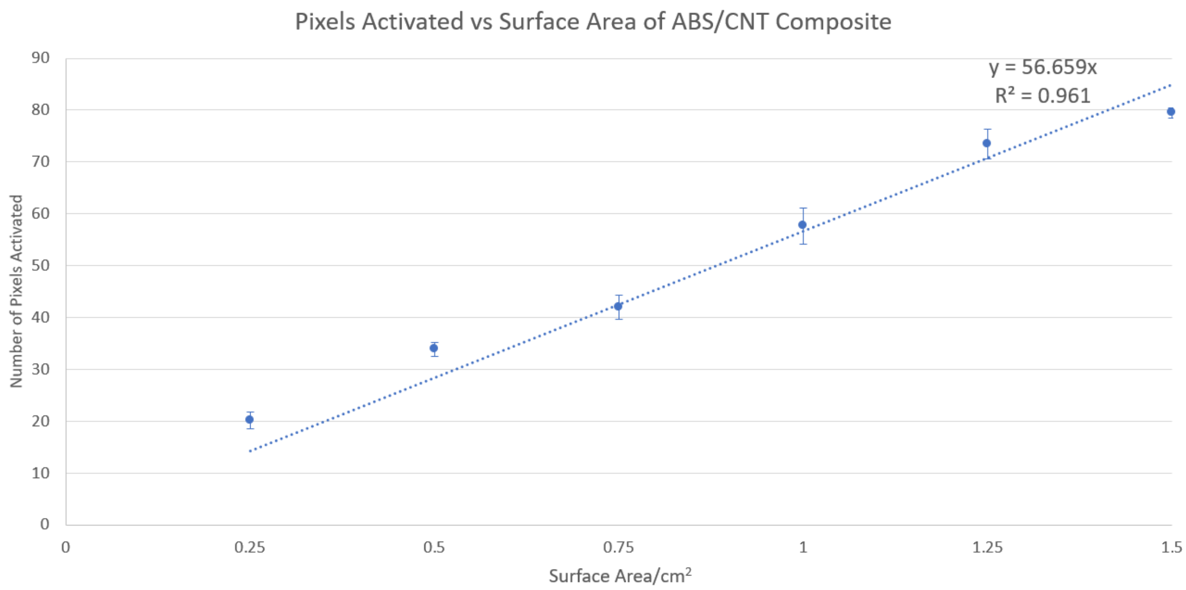

Fig. 6: Graph of average number of pixels activated against surface area of ABS/CNT composite

An increasing linear trend between the surface area of the ABS/CNT and the number of pixels activated on the touchscreen is observed, with the equation $y=56.659x$. The good fit of the linear trendline with an R^2 value of 0.961 indicates that each increase of a unit surface area of the ABS/CNT adds the same amount of charge, regardless of existing surface area, thus the surface area of the ABS/CNT can be accurately correlated with capacitance. A higher surface area provides better contact between the screen and ABS/CNT, which is essential for the activation of the touchscreen as a higher surface area in contact increases the capacitance between the ABS/CNT and the electrodes in the touchscreen, allowing the sensors to detect the change in capacitance and hence the swipe motion more easily. As such, the surface area of the ABS/CNT has a considerable impact on the effectiveness of the interface of the touchscreen, which affects the sensitivity and thus user experience.

4.2.2 Velocity of Finger

To examine the efficacy of registration of swiping motions at different velocities, 6 readings were taken for each velocity of the finger used (Table 2 in Appendix F). The surface area of the ABS/CNT used was 0.75cm^2.

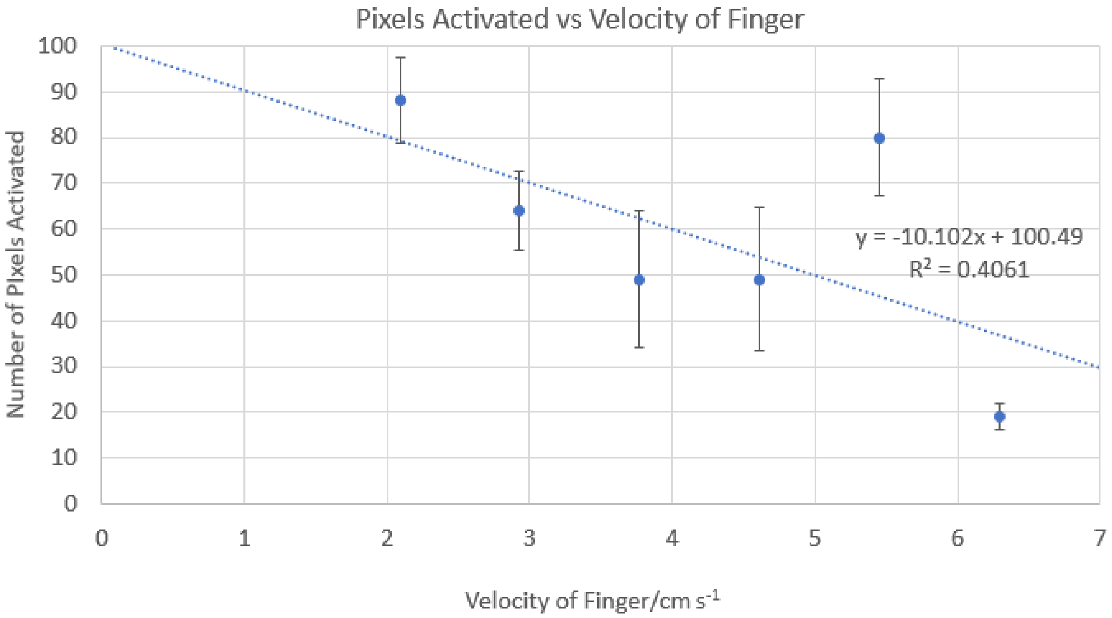

Fig. 7: Graph of average number of pixels activated against velocity of finger

Overall, a decreasing linear relationship between the number of pixels activated and the velocity of the finger can be observed, which is expected as lower velocities provide more time for the finger to activate the touchscreen. However, the large variance in the results, as indicated by the large error bars, suggests that slipping occurs as the finger slides across the touchscreen, which adversely affects the consistency of the contact between the finger and the touchscreen. Hence, while other conductive 3D-printable composites such as ABS/Graphite may provide a higher conductivity and hence better activation of the touchscreen, these materials are less suitable due to greater slippage that can affect the user experience.

5. FUTURE WORKS

Based on our current signal processing methodology, unique peaks must be identified for every patient since each person's EMG data are unique and vary widely with the amount of body fat, body hair, sweat and random physiological conditions [13]. Alternatively, a significant number of datasets can be collected and analysed using machine learning to identify patterns across the population. Either way, many datasets must be collected to achieve a suitable accuracy (>90%). Additionally, although the Myo armband has a low sampling frequency of 200 Hz as compared to typical clinical EMG sensors with sampling frequencies of ≥1000Hz [14], the inertial measurement unit (IMU) data, which includes readings from a 3D gyroscope, 3D accelerometer and a magnetometer, can be collected from the armband to more accurately identify hand gestures.

Patients must also be trained to use the hand, so an application where patients uses the residual muscles to play a game will be useful to help patients use the hand, similar to ADAPT-MP games [15]. Fingerprints can be incorporated onto the finger pads to serve as identification and also increase the friction to reduce slippage.

Finally, a feedback system will engage the extra-prioceptive system of the patient and achieve two key goals of prosthetic hand: approximating the feeling of touch that a real hand will have [16], and perform actions in a more coordinated manner and with less visual attention [17]. The conductive ABS/CNT network thus provides a suitable platform to attach an array of sensors to a microcontroller to create an effective feedback system.

To measure the functionality of the prosthetic hand, clinical tests such as the Southampton Hand Assessment Procedure [18] can be run on the completed hand. These tests would show the abilities and limitations of the hand in executing crucial motions, which would allow the hand to be compared with commercial products and be improved.

6. CONCLUSION

Using the Myo armband to read the EMG signals from the patient's arm gives accurate results with a low TER of 10%, so this is a viable method that can achieve higher patient acceptance. This thus offers a low-cost solution to read patients' desired motions as they attempt to perform them, which is the first step of allowing them to move their prosthetic hand.

For the finger to effectively interface with touchscreens, it is important that the user is able to make precise motions, and so the lower the surface area of the ABS/CNT composite, the smaller the number of pixels activated, making their movements on the touchscreen more precise and less confusing for the device to interpret. At the same time, the greater the surface area of the composite, the greater the capacitance, which increases sensitivity. In addition, different devices may also have different minimum surface areas of conductive material they can respond to, as they are designed to ignore accidental touches. Hence, a balance must be struck in determining the optimal surface area of ABS/CNT to be printed on the fingertips to optimise the user experience.

Overall, 3D-printing and careful design can allow a hand to be produced, with the functionality of high-end commercial hands at the fraction of their cost, which will benefit many upper limb deficiency patients.

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APPENDIX A

Fig. 1a: Back view of the prosthetic hand

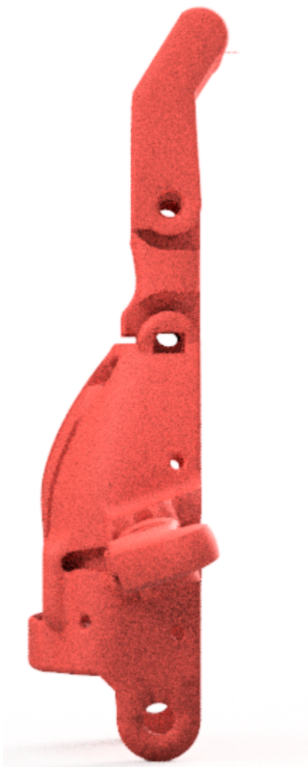

Fig. 1b: Side view of the prosthetic hand

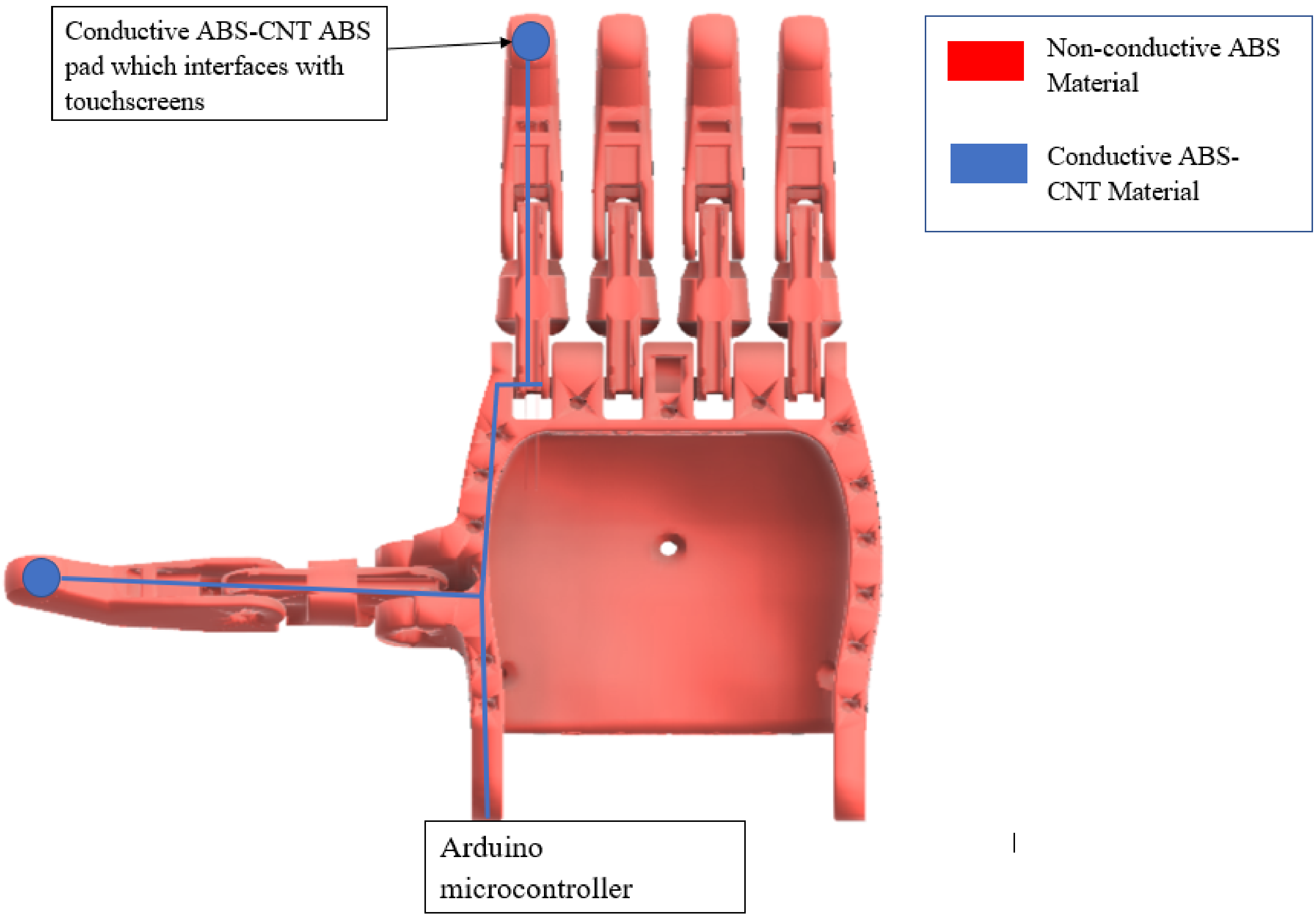

Fig. 1c: Model of the prosthetic hand with connections

APPENDIX B

Fig. 2: Myo armband

APPENDIX C

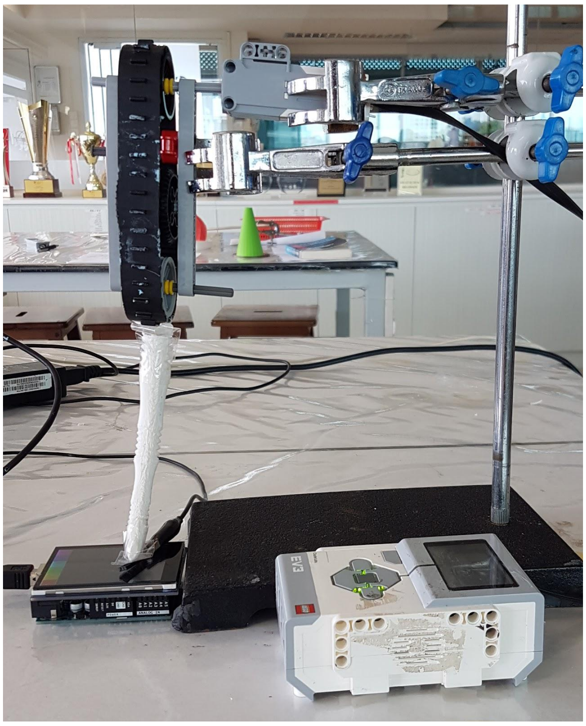

Fig. 3a: Lego Mindstorms setup

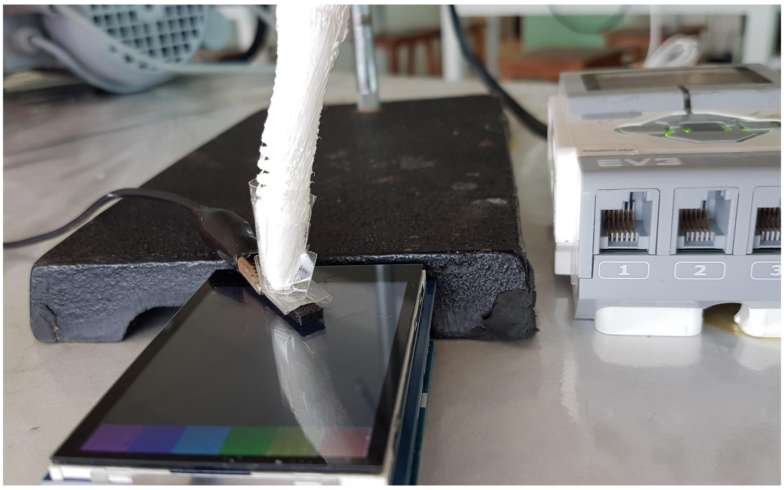

Fig. 3b: Close-up view of setup

APPENDIX D

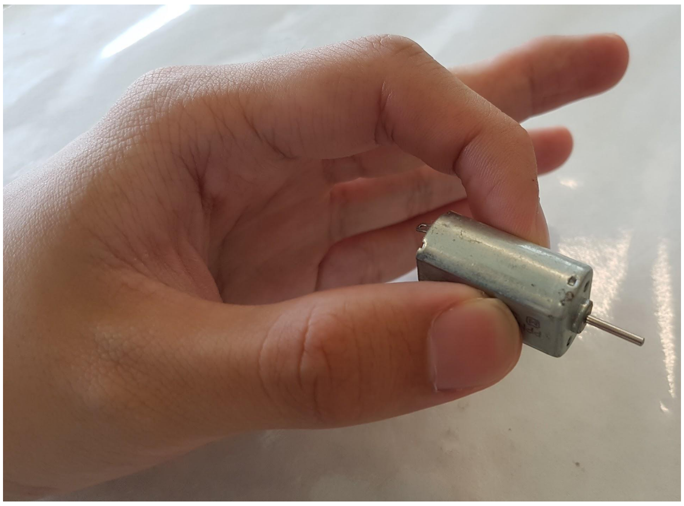

Fig. 4a: Precision grip (pinching motion)

Fig. 4b: Power grip (clenching motion)

APPENDIX E

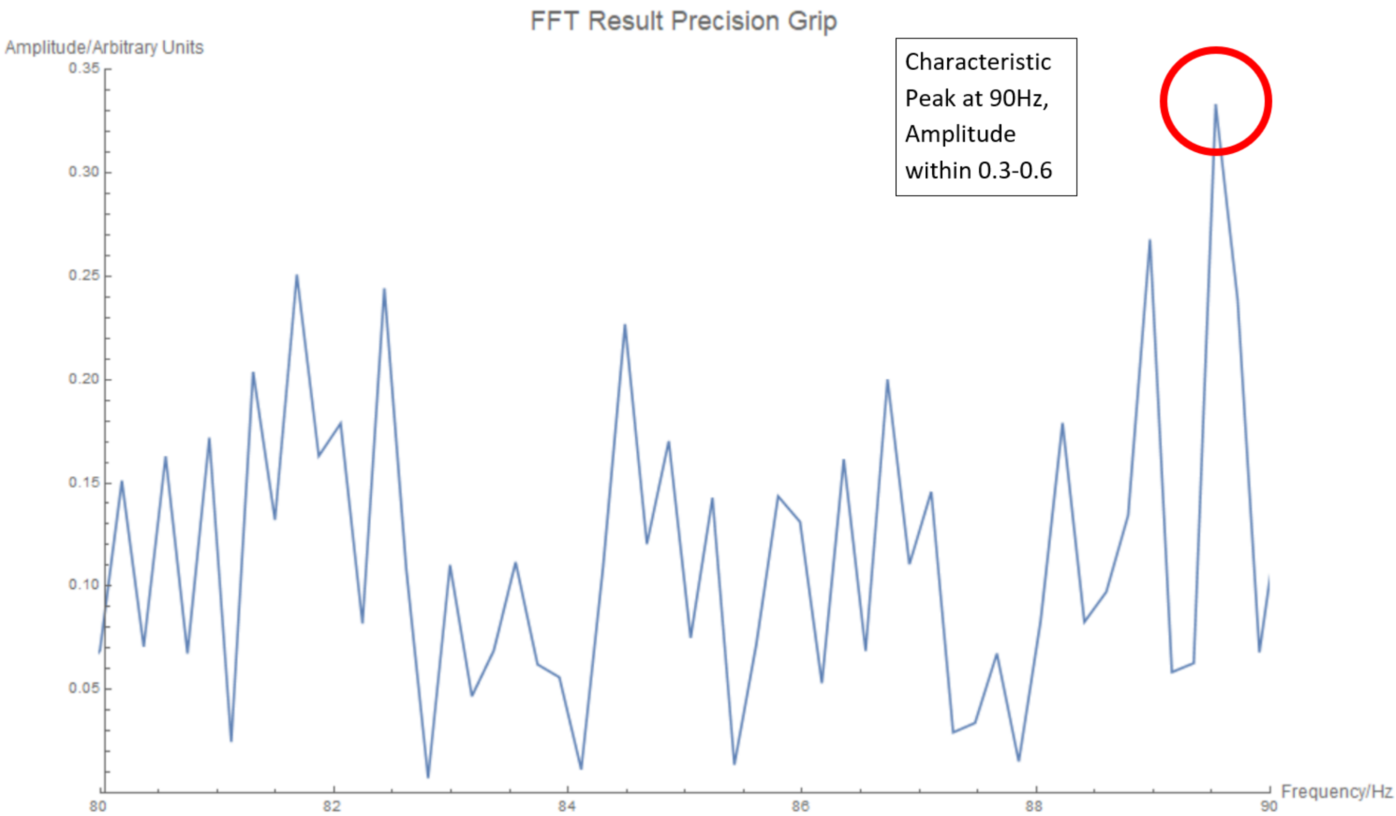

Fig. 5a: FFT results for the precision grip after filtering

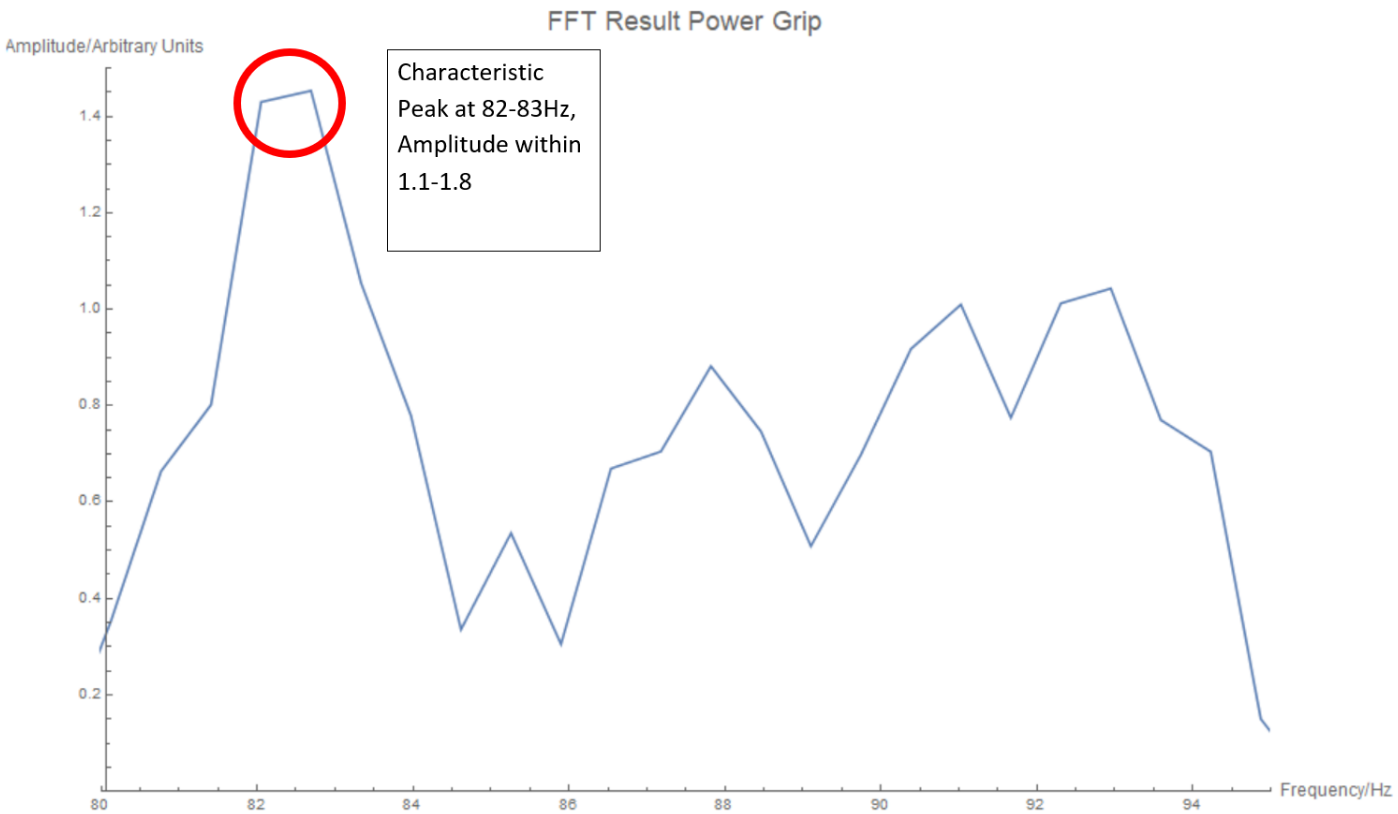

Fig. 5b: FFT results for the power grip after filtering

Fig. 5c: FFT results for the swiping motion after filtering

APPENDIX F

Table 2: Results for activation of pixels using different surface areas of ABS/CNT

Surface Area of ABS/CNT /cm^2	Number of Pixels Activated						
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Average
0.25	16	39	23	15	15	13	20
0.50	48	30	36	35	32	22	34
0.75	27	35	37	67	48	38	42
1.00	56	78	35	87	53	37	58
1.25	65	59	61	65	96	95	74
1.50	78	78	74	74	88	85	80

Table 3: Results for activation of pixels using different velocities

Velocity of finger/cm s^{-1}	Number of Pixels Activated			
	Trial 1	Trial 2	Trial 3	Average
2.09	101	70	93	88
2.93	59	52	81	64
3.77	60	20	68	49
4.61	80	33	33	49
5.45	57	82	101	80
6.29	18	14	24	19