Report

1. INTRODUCTION

The World Health Organisation estimates that 30 million people worldwide require prosthetic limbs. However, more than 80% of patients in developing countries could not afford prosthetics [1]. Furthermore, the prohibitive cost of advanced prosthetics causes many patients to turn towards cheaper models which are often incompatible due to the limited functionality of their sensor system. Hence, our aim is to develop our own cost-effective electromyography (EMG) sensor system to increase the functionality of cheaper prosthetic hand models.

2. LITERATURE REVIEW

2.1 Current EMG Sensor Systems

The formerly commercial EMG sensor system used in our experiment is the Myo Armband (Figure 1) which uses stainless steel electrodes connected to their own EMG sensors and an Inertial Measurement Unit (IMU) to wirelessly control technology with hand gestures [2]. However, it was not affordable for those in developing countries and is now out of production. Unfortunately, other EMG systems are expensive and do not come with gesture classification, meaning those in need of affordable and controllable prosthetics would have to create their own EMG system from scratch.

2.2 Current Electrodes

The most commonly used electrodes for measuring EMG signals are standard wet silver/silver chloride (Ag/AgCl) electrodes (Figure 2) as found in hospital-based medical diagnostic and home health monitoring systems. In order to reduce the skin contact impedance, these electrodes typically require electrolytic conductive gel and cleaning the patch of skin [3]. Though the standard wet Ag/AgCl electrodes have good signal stability and reproducibility due to lower impedance, the use of the conductive gel is a significant drawback as it dries out over time, significantly affecting signal quality and making such wet electrodes non-reusable [4]. In addition, some patients could also develop skin irritation or allergic rashes [3,5].

Thus, our dry electrodes will be 3D printed for long-term usage. Dry electrodes perform similarly to conventional wet electrodes and performs better when the subject is in motion [4]. Furthermore, 3D-printing offers a more cost effective solution, with 3D-printed electrodes being much less expensive, more customisable and lightweight. Our electrodes will be 3D-printed using the conductive material ABS/CNT, a novel acrylonitrile butadiene styrene/carbon nanotube (ABS/CNT) composite created by Zhong, Lin, Chor and Tan [6],

2.3 Typical Method for Gesture Classification

2.3.1 Discrete Fourier Transform (DFT)

When a muscle group is activated, it exhibits an oscillating electric potential that can be picked up by electrodes as EMG signal data. Discrete Fourier Transform (DFT) is often used to decompose these signals into component frequencies which are then used for classifying gestures [7]. According to the Nyquist-Shannon Sampling Theorem [8], all DFT algorithms have a limited frequency resolution, which is the frequency range of each discrete component. The max resolution is the sampling frequency divided by the number of raw samples used for DFT, with the highest detectable frequency being half the sampling frequency.

2.3.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is normally used to extract information from EMG signal data for classification [7]. PCA calculates Principal Components (PCs) from the component frequencies of the EMG signal, reducing the number of features used to represent the signal data. This in turn removes uncorrelated information while creating features that accentuate differences between EMG signal data, making it easier to classify.

2.3.3 Linear Support Vector Classifier (SVC)

Based on Russo, R. E. et. al. research, the Linear Support Vector Classifier (SVC) is the most accurate at classifying EMG signals since there are few EMG data samples for training [9]. Linear SVCs use multi-dimensional planes to divide data points into regions according to their label. It then classifies a new data point by the region it falls into.

3. METHODOLOGY

3.1 3D-Printed Dry Electrode Design

The button design on the bar electrodes is based on Myoware-compatible 3M electrodes, such that the button can clip onto the Myoware sensors (Figure 3). Since the specific dimensions of 3M's wet electrode are unknown, the button was created based on the measurements made using a vernier caliper (Figure 4). To account for the uncertainty of the measurements of the vernier caliper and the precision of the 3D printer, 4 different button sizes (2.8mm, 2.9mm, 3.0mm, 3.1mm) were printed. After testing how well each button fits by clipping them onto the Myoware sensors, 3.1mm was decided upon as the final size for button electrodes. The button design is then merged with bar electrodes such that the bar electrode can be attached to the myoware sensor (Figure 5). Bar electrodes are optimal for collection of muscle signal data when aligned correctly to the muscle [7]. The dimensions of the bar of are 40mm×10mm×0.65mm chosen for our experiments are based on work done by Guler et al. [7].

To increase the conductivity of the bar electrodes, they will be painted with conductive 60% silver ink. The dip coating method that worked well as shown by Papatheodorou et al.'s work [10] was adapted for our experiments. Dip coating was conducted on the 3D-printed electrodes by soaking them into $60cm^3$ of sodium hydroxide solution ($0.100mol/dm^3$ concentration) for 20 seconds and then rinsing it with running tap water. Afterwards, the electrodes are soaked into $60cm^3$ of solution comprising of 10% tap water, 65% sulfuric acid ($0.100mol/dm^3$ concentration) and 25% nitric acid ($0.100mol/dm^3$ concentration for 20 seconds). The electrodes are then put through distilled water, then boiling water, then dried to remove the solution. The above procedures will remove the impurities and ensure a clean surface for coating. Both sides of the electrodes are then coated with silver paint using clean paint brushes, as this is the most conventional method to ensure even layers of thin coating. 5 layers of silver ink were coated on both sides of the bar electrodes (Figure 6).

3.2 Mounting of Sensors

4 Myoware sensors were mounted on 4 different muscle groups, resulting in 4 channels of signal data. 4 sensors were utilized as a compromise between comfort and classification accuracy. Since there are no literature review that suggests the placement of the 4 myoware sensors on the forearm, placements was decided based on existing literature review that utilizes 2 myoware sensors on wrist and 2 myoware sensors on the forearm [11, 12, 13]. The placement of the Myoware sensors on the arm can be seen in Figure 7A, 7B, 8A, 8B. Tape was utilized in the case of the dry electrodes to ensure that the electrodes would stay in place and in good contact with the subject's skin. The sensors were connected to the high quality 12-bit Analog to Digital Converter (ADC) of the ESP32 microcontroller. Due to the

size of the Myo Armband, it was worn near the wrist during the experiments, thus the data collection took place at the wrist (Figure 9).

3.3 Data Collection

The 3 types of gestures used for data collection are clenched-fist, spread-hand and at rest. These are the essential actions required for prosthetic hands to execute important daily activities, such as holding and carrying objects. Raw EMG signal data is collected within a 10 second period, of which there are 16 of these periods for each of the 3 gestures, with 5 second rests between each period. The signal data consists of many samples, which are discrete measurements of the muscle's electric potential, taken many times per second at a sampling frequency.

3.4 Data Processing

3.4.1 Signal Processing

During the earlier Data Collection, per gesture classification period, 2048 samples are collected when using a sampling frequency of 200Hz. Since 16 periods are conducted for each of the 3 gestures, there is a total 32768 raw samples for each gesture. To obtain processed samples, DFT is applied to raw samples with a fixed DFT batch size. For example, using a DFT batch size of 128, there will be 32768 ÷ 128 = 256 processed samples per gesture. When using a sampling frequency of 2000Hz, because both samples collected per gesture classification period and DFT batch size are multiplied by 10, the number of processed samples per gesture remains constant. Likewise, the frequency resolution between 200Hz and 2000Hz datasets are kept constant. The choice of using 200Hz and 2000Hz is explained later in section 3.5.

3.4.2 Accuracy Calculation

Processed samples are split into shuffled train and test datasets with a ratio of 3:1 and with an equal distribution of the 3 gesture samples in both. The datasets are then used to train and test the classification algorithm to obtain the classification accuracy. The classification algorithm used is the SVC based bagging ensemble. However, since the datasets are shuffled and the classification algorithm is initialised randomly, splitting of datasets and training of classifier is repeated 1000 times to get 1000 accuracy scores, allowing the calculation of an overall accuracy that is less vulnerable to random chance. The mean accuracy is utilized as the raw accuracies follow a normal distribution (Figure 10) and have a small standard deviation of around 1%.

3.4.3 Parameter Tuning Method

Parameter tuning is done to account for the different EMG setups having optimal accuracy using different parameter values, allowing for a fairer comparison than if the parameters were standardized. The parameters tuned are the frequency resolution and number of Principal Components (PCs) used in PCA. Powers of 2 are used for the number of PCs while the DFT batch sizes are based on having the same frequency resolution. Accuracies for the various parameter configurations for each EMG setup can be found in the appendix.

3.4.4 Selection of Classifier

To find the optimal classifier for EMG data, testing was conducted using the Myo Armband. After testing all the classifiers from Scikit Learn's Python Library [14], Bagging Ensemble based on linear SVC achieved the highest accuracy of 83.5% (Figure 11). Bagging Ensemble trains multiple instances of SVC on random subsets of the dataset and then aggregates the individual predictions, allowing it to train faster [14]. Hence, it was selected as the classifier over pure SVC despite only have a slightly higher accuracy.

3.5 Experiments

There are 4 main experiments. In the first experiment, the classification accuracy of sampling at 200Hz versus 2000Hz is collected using 4 Myoware sensors with wet electrodes. In the second experiment, the individual accuracy of the 4 Myoware sensor placements is collected to better understand how the classification algorithm classifies gestures. In the third experiment, the accuracy between wet electrodes and our dry electrodes is compared to analyse how well our dry electrodes perform compared to the commercial wet electrodes. In the fourth experiment, the accuracy using different frequency resolutions and numbers of PCs in PCA is collected in order to analyze how the classification system should be optimized.

4 RESULTS & DISCUSSION

4.1 200Hz versus 2000Hz Sampling Frequency

The wet electrode setup on the inner wrist muscle group achieves 97.3% on the 2000Hz dataset (Figure 12) and 45.1% on the 200Hz dataset (Figure 13). According to the Nyquist-Shannon Sampling Theorem [8], using 2000Hz compared to 200Hz, the frequency range is 0-1000Hz compared to 0-100Hz. From our results, it can be seen that the greater frequency range reveals more information about the gestures compared to the smaller frequency range. This is due to the range of EMG signal frequencies which is 50Hz to 400Hz [9]. Our classifier has access to more features for classifying gestures, resulting in a greater accuracy. However, the Myo Armband is still able to attain a comparatively high accuracy of 83.5% (Figure 14) despite having only a 0-100Hz range. This might be due to it having a significantly higher count of 16 channels, resulting in larger EMG signal data collection. However, the actual reason is difficult to discern as the Myo Armband is closed source.

4.2 Accuracy of the four Sensor Placements

Using the wet electrode setup, each sensor placement was tested individually for their gesture classification accuracy. The inner wrist uses the flexor digitorum profundus muscle which is used to flex fingers [15]. Thus the inner wrist obtained the highest accuracy of 97.3% (Figure 12) due to the heavy usage of the fingers in the motion of the three gestures. The outer wrist position uses the extensor digitorum muscle which provides extension for the fingers excluding the thumb [15]. This suggests similarity in performance to the flexor digitorum profundus. However, it only obtains an accuracy of 65.8% (Figure 15) and is the 3rd best among the 4 placements. As it only performs extension for 4 fingers, there is insufficient information obtained to distinguish the rest-position gesture from the clenched-fist gesture.

The inner forearm position uses the flexor carpi radialis muscle which aids the wrist in bending inwards and to the sides [15]. Our 3 gestures do not utilize much of the said motion and thus it has the lowest accuracy of 63.5% (Figure 16). The outer forearm position uses the extensor carpi radialis longus muscle which helps extend the hand at the wrist joint [15]. It achieves the 2nd highest accuracy of 70.4% (Figure 17) as both the clenched-fist and spread-hand gestures involve the extension of the hand.

4.3 Dry versus Wet Electrodes

Wet electrodes perform better than dry electrodes due to reduced skin impedance [16]. Our dry electrodes performed worse than expected (Figure 18). The highest accuracy of the dry electrodes yielded 41.7% compared to the wet electrodes with a highest accuracy of 95.1% (Figure 19). However, dry electrodes are more practical as they are more durable and reusable as they do not dry out unlike wet electrodes. The accuracy of the wet electrode setup utilising all 4 sensor placements is less than using the inner wrist alone at 95.1% versus 97.3% (Figure 12). However, the dry electrodes performed differently, achieving 37.6% using only the inner wrist (Figure 20) and 41.7% when using all four sensors. The classification algorithm could be fairly considering each sensor placement thus leading to a lower overall accuracy compared to the accuracy of single best placement (Section 4.2) at the inner wrist. However as the data collected for dry electrodes has more signal noise than wet electrodes, every placement is essential to classifying the gesture.

4.4 Best Parameters for Data Processing

Myo Armband, wet and dry electrode setups have optimal accuracies using different tuning configurations (Figure 14, 18, 19). Using low (2-4) PCs for PCA generally results in poorer accuracy for the wet and dry electrode setups. Additionally using more (>6) PCs results in an accuracy decrease for both the Myo Armband and wet electrode setups. This is because a larger number of PCs can remove more signal noise thus providing more features for the classifier to select and classify. However there is a trade-off. If there are too many PCs, the classifier gets distracted by less relevant PCs, decreasing the accuracy. Thus the dry electrode setup performs better with more PCs due to the data having significantly more signal noise [16] compared to the wet electrode setup which performs better with less PCs due to less signal noise. However, the Myo Armband which also utilizes dry electrodes achieved optimal accuracy using a low number of PCs. This could be due to the Myo Armband having 16 channels, thus it is able to provide targeted raw EMG data, hence requiring far less PCs to classify accurately.

5. CONCLUSION

In conclusion, our classifier system yielded a 95.1% accuracy on the wet electrode setup as compared to the Myo armband which yielded an 83.5% accuracy. This shows the good performance of our classifier. Our dry electrode setup yielded a 41.7% accuracy which is better than random chance at 33.3%. However, this could be due to the use of ABS/CNT instead of more conductive and flexible materials for our electrodes, resulting in the large accuracy difference between wet and dry electrodes. Therefore, future work such as coming up with better dry electrode designs utilising more suitable material that could reduce skin impedance, could be done to improve the classification accuracy. Overall, our research shows that it is possible to create a low-cost replacement to the Myo Armband that will perform better given further research into effective dry electrode designs that can match the performance of wet electrodes.

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Appendix

Figure 1: Myo Armband

Figure 2: Commercial 3M wet electrodes

Figure 3: Myoware sensor hub

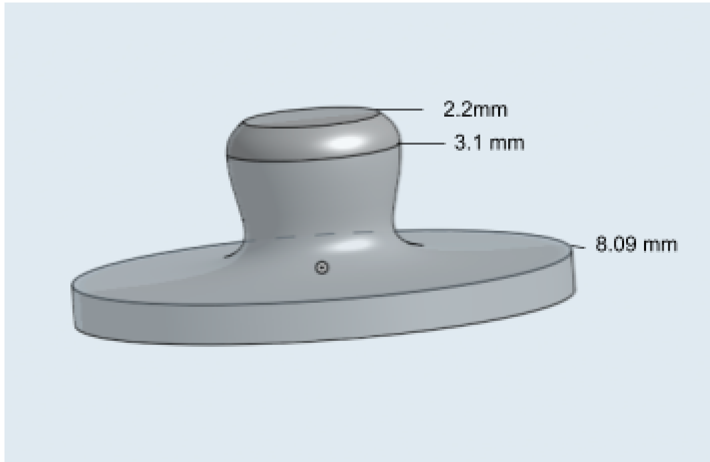

Figure 4: Blueprint and Dimensions of button design

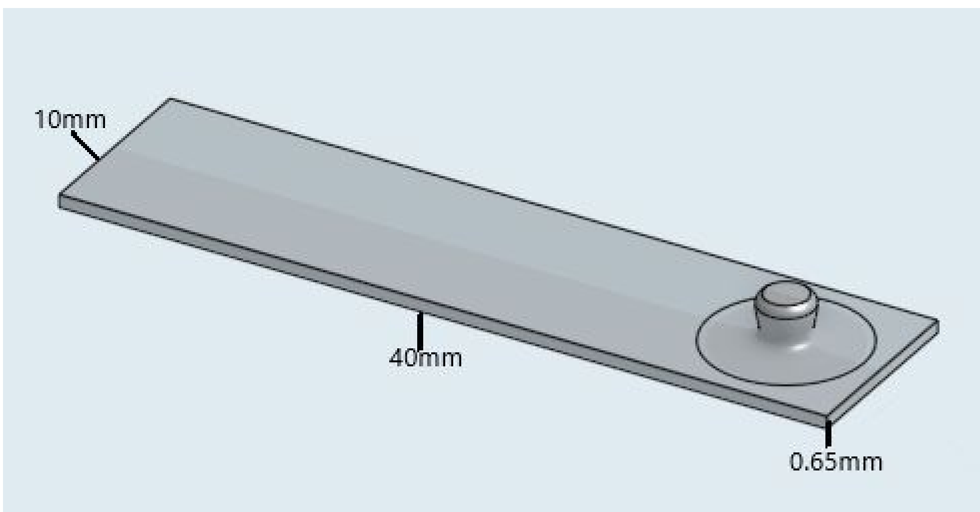

Figure 5: Blueprint and Dimensions of 3D-Printed Bar Electrode

Figure 6 : 3D-Printed Bar Electrode coated with silver ink

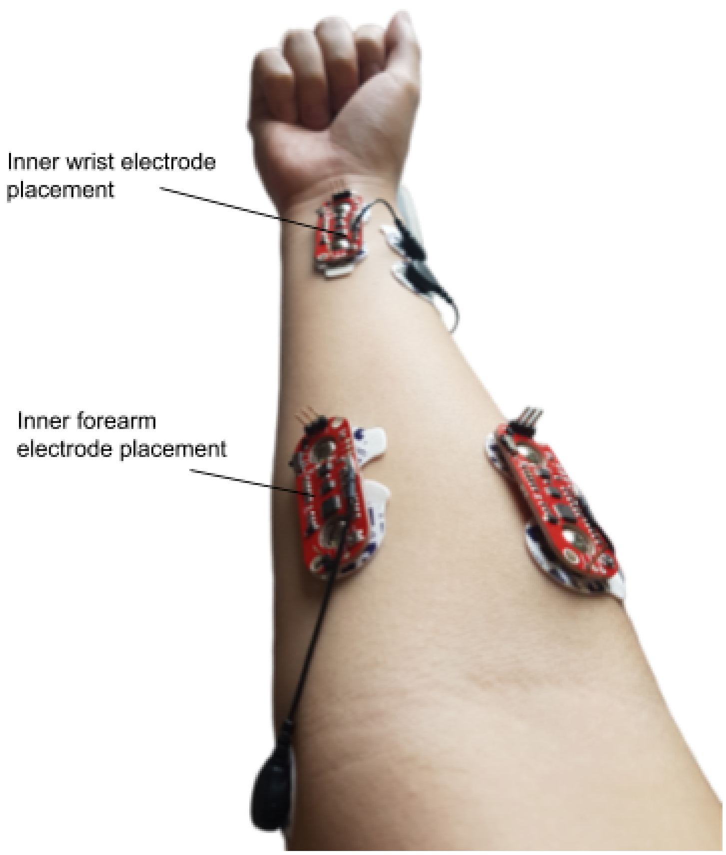

Figure 7A: Inner arm placement of Wet electrodes

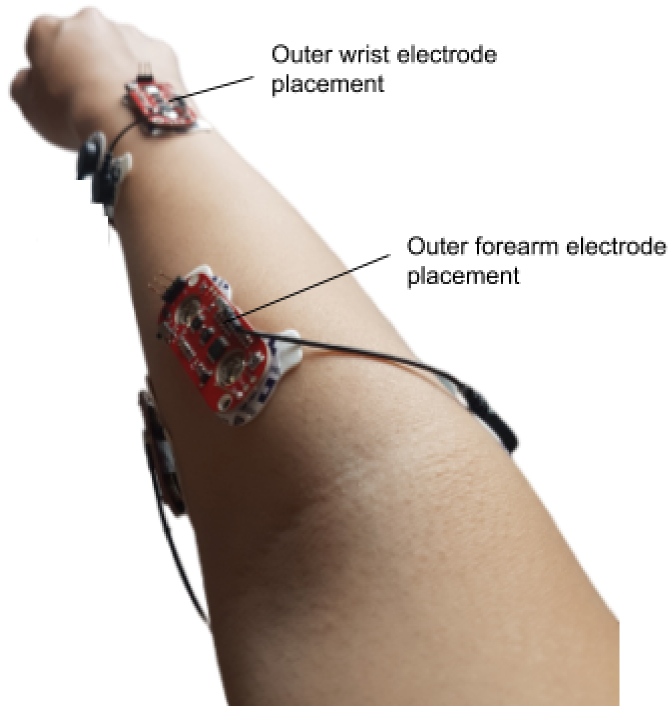

Figure 7B: Outer arm placement of Wet electrodes

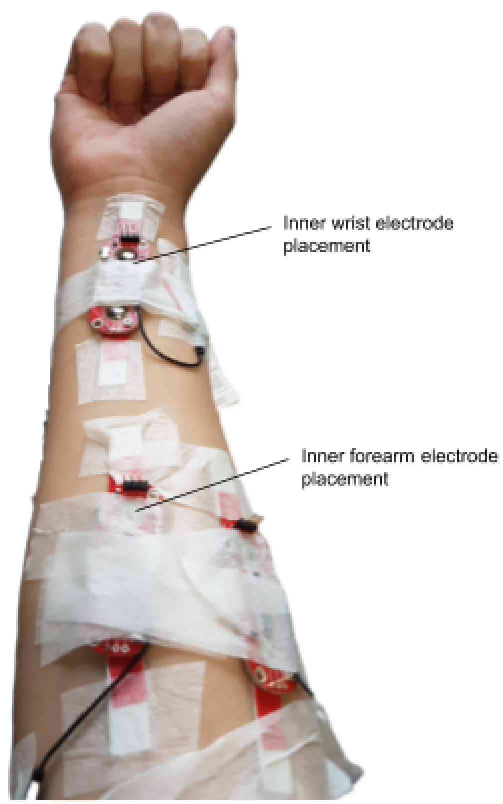

Figure 8A: Inner arm placement of Dry electrodes

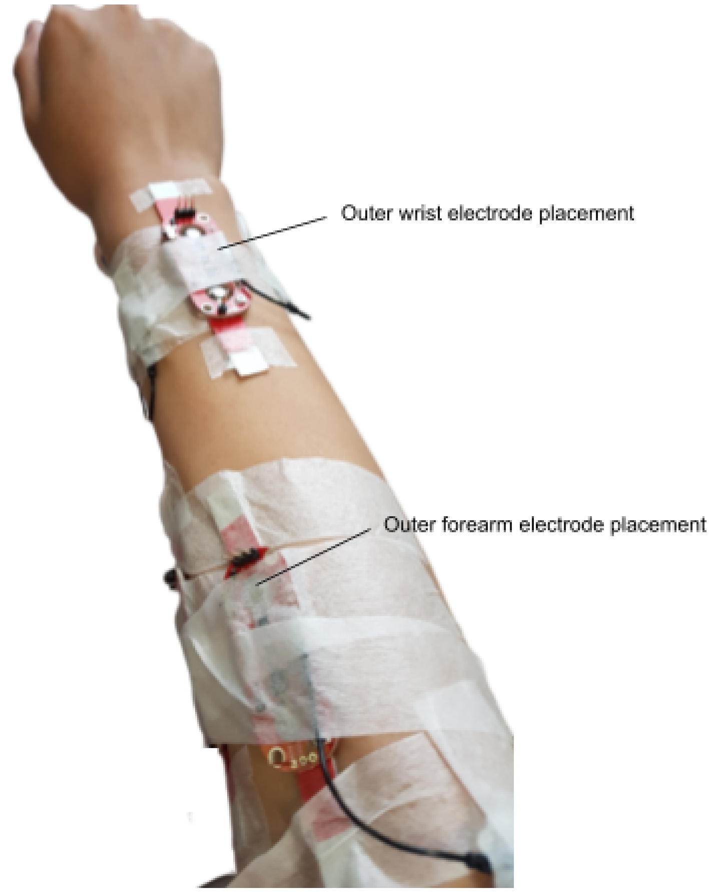

Figure 8B: Outer arm placement of Dry electrodes

Figure 9: Placement of Myo Armband

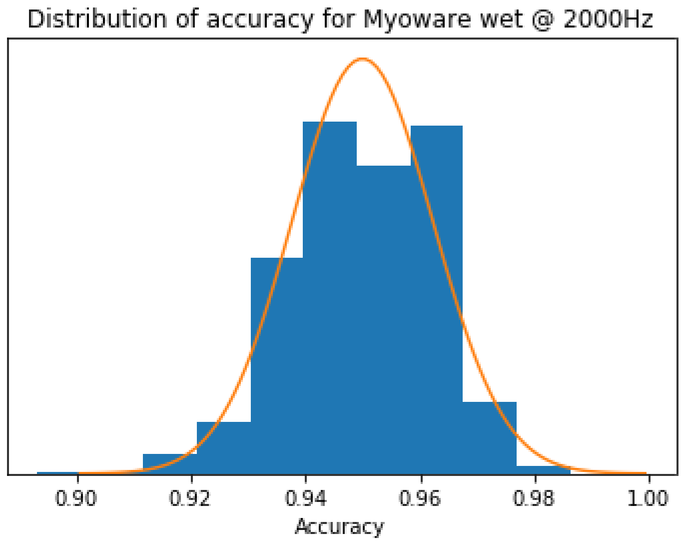

Figure 10: Distribution of Classification Accuracy over 1000 random runs

Myo Armband @ 200Hz	
Classifier	Accuracy
Random Forest Ensemble	55.9%
Decision Tree	74.1%
Tree-based Bagging Ensemble	80.0%
Linear Support Vector Machine	82.9%
Extra Trees Ensemble	53.2%
Linear Support Vector Machine based Bagging Ensemble	83.5%

Figure 11: Table of Results of Classifiers using Myo Armband

Wet inner wrist @ 2000Hz		Number of Principal Components				
Range of each DFT bin	used per DFT Sample	2	4	8	16	32
6.250000Hz	320	74.275%	93.053%	93.385%	93.176%	93.183%
3.125000Hz	640	67.721%	96.192%	96.182%	95.942%	95.744%
1.562500Hz	1280	62.854%	96.917%	97.266%	97.255%	95.912%

Figure 12: Table of Results of MyoWare Wet Electrodes at 2000Hz placed at inner wrist

Wet inner wrist @ 200Hz		Number of Principal Components				
Range of each DFT bin	used per DFT Sample	2	4	8	16	32
6.250000Hz	32	43.996%	43.921%	43.701%	43.667%	42.564%
3.125000Hz	64	45.097%	44.560%	44.860%	43.661%	42.942%
1.562500Hz	128	44.731%	44.636%	44.029%	43.204%	42.883%

Figure 13: Table of Results of MyoWare Wet Electrodes at 200Hz placed at inner wrist

Myo Armband @ 200Hz		Number of Principal Components					
Range of each DFT bin	used per DFT Sample	2	4	8	16	32	64
6.250000Hz	32	61.880%	61.690%	64.749%	64.528%	63.149%	60.019%
3.125000Hz	64	65.718%	75.581%	75.703%	72.431%	67.311%	58.993%
1.562500Hz	128	82.721%	**83.497%**	81.347%	76.656%	67.777%	63.694%

Figure 14: Table of Results of Myo Armband at 200Hz

Wet outer wrist @ 2000Hz		Number of Principal Components				
Range of each DFT bin	used per DFT Sample	2	4	8	16	32
6.250000Hz	320		33.619%	62.512%	64.927%	65.789%
3.125000Hz	640		33.815%	33.738%	57.038%	61.543%
1.562500Hz	1280		34.515%	34.299%	34.399%	56.057%

Figure 15: Table of Results of MyoWare Wet Electrodes at 2000Hz placed at outer wrist

Wet inner forearm @ 2000Hz		Number of Principal Components				
Range of each DFT bin	used per DFT Sample	2	4	8	16	32
6.250000Hz	320		33.354%	33.361%	59.595%	63.467%
3.125000Hz	640		32.828%	32.747%	32.711%	55.088%
1.562500Hz	1280		31.824%	32.390%	32.139%	46.313%

Figure 16: Table of Results of MyoWare Wet Electrodes at 2000Hz placed at inner forearm

Wet outer forearm @ 2000Hz		Number of Principal Components				
Range of each DFT bin	used per DFT Sample	2	4	8	16	32
6.250000Hz	320		33.983%	57.204%	58.927%	70.447%
3.125000Hz	640		34.547%	48.997%	50.488%	52.562%
1.562500Hz	1280		36.980%	40.031%	39.419%	41.046%

Figure 17: Table of Results of MyoWare Wet Electrodes at 2000Hz placed at outer forearm

Myoware dry electrodes @ 2000Hz		Number of Principal Components					
Range of each DFT bin	used per DFT Sample	2	4	8	16	32	64
6.250000Hz	320	35.217%	36.244%	37.044%	39.535%	40.439%	**41.724%**
3.125000Hz	640	36.310%	37.774%	37.932%	39.422%	39.254%	39.004%
1.562500Hz	1280	37.154%	39.735%	39.222%	39.339%	38.327%	36.901%

Figure 18: Table of Results of MyoWare Dry Electrodes at 2000Hz

Myoware wet electrodes @ 2000Hz		Number of Principal Components					
Range of each DFT bin	used per DFT Sample	2	4	8	16	32	64
6.250000Hz	**320**	33.302%	36.106%	93.437%	93.991%	94.306%	94.121%
3.125000Hz	**640**	34.338%	36.350%	89.518%	**95.137%**	93.925%	91.155%
1.562500Hz	**1280**	37.550%	37.250%	79.910%	91.574%	89.115%	83.495%

Figure 19: Table of Results of MyoWare Wet Electrodes at 2000Hz

Dry inner wrist @ 2000Hz		Number of Principal Components				
Range of each DFT bin	used per DFT Sample	2	4	8	16	32
6.250000Hz	**320**		36.071%	35.770%	35.447%	35.261%
3.125000Hz	**640**		36.524%	35.861%	35.180%	35.640%
1.562500Hz	**1280**		34.563%	35.352%	35.069%	37.624%

Figure 20: Table of Results of MyoWare Dry Electrodes at 2000Hz placed at inner wrist