

Robust control of hand prosthesis using electromyography, accelerometers and gyros

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Preface

This project was performed at the department of biomedical engineering, faculty of engineering Lund University during the spring and autumn term of 2016. The project was supervised by Christian Antfolk and Frida Sandberg acting as examiner.

This project would not have been possible without the help of several people, I would like to thank my supervisor Christian Antfolk for valuable insight and help during the project. In addition, I would also like to thank all the volunteers who generously gave some of their time to help test the program created by this project; Tobias Svensson, Ingrid Svensson, Elin Holmström, William Rosengren, Dzenan Hjarovic, Paul Lidgard, Johan Andersson and Oskar Ström.

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Abstract

The goals of this project are to investigate the viability of using the Myo™ armband developed by Thalmic labs as a tool for myoelectric control of a hand prosthesis as well as investigate whether the armbands ability to record its spatial position and orientation can be used to increase the performance of the prosthesis control program. Using the surface electrodes, gyroscopes and accelerometers of the Myo™ armband, a control system for myoelectric control of a hand prosthesis was created and tested on nine different users. The system recognizes eight different hand gestures and uses an artificial neural network as classification tool.

The system was evaluated by two main criteria; gesture classification accuracy and response time. Offline testing showed an average gesture classification accuracy of over 90%, however, the accuracy was greatly reduced in online testing and a great variance in accuracy between different gestures was observed. Likely in large part caused by user inexperience with the system. The average system response time for all gestures was in the range of 100-200ms, again, with variations between gestures.

Using positional data in addition to the myoelectric signals recorded by the armband showed no significant improvement in accuracy in best case scenarios and a greatly reduced accuracy in worst case scenarios, while the use of positional data still has the potential to improve the performance of a prosthesis control system the wrong approach to do so was likely chosen in this project and positional data was excluded in the final version of the program, using instead only myoelectric data for classification.

Background

The hand is a complex part of the human anatomy. Consisting of a large number of small bones, tendons, sinews and muscles it creates a mean for us to interact with and gain information from our environment throughout daily life. Using our hands for all manner of different tasks is something we learn from the moment we are born and it remains a natural way of interacting with our surroundings for the rest of our lives. Considering this, it is no great surprise that the loss of a hand or even just parts of it has a

great impact on daily life. The loss of a hand results in more than just the direct loss of function, it also a psychological stress and great effort is required to adept to this new situation. There are also other consequences, in many cases persons who lose their hand are unable to continue in their current profession and are forced to find another or retire entirely [1].

Finding exact numbers on the amount of people currently living with this kind of limb loss is difficult, an old survey from 1996 that has since stopped found that approximately 1.2 million Americans were living with the loss of a limb. Estimations point to a number around 1.6 million in 2005 [2]. A survey done in Norway and Sweden over a 10 year period showed that the incidence of partial hand amputation is 1.9 per 100 000 people per year with a significantly higher risk in left handed persons [3].

In these cases, the only treatment available is the use of a prosthesis to replace the lost limb and restore some of the lost function of the hand. A hand prosthesis may be designed in many different ways and their ability to restore function also varies greatly. Some models are very simple and have a primarily aesthetic function while doing little to restore the function of the lost limb. More advanced models can consist of a simple muscle powered "claw" capable of a gripping motion which, while useful, is a far stretch from the actions a regular hand can perform and often do not visually resemble a real hand [4, 5], see examples in figure 1. Modern technology allows for more complex devices using myoelectric control, recording and using the electric signals of the nervous system to control motors in the prosthesis, that more accurately mimic a real hand. These modern models show a promising future for people living with limb loss although there is still a long road ahead before a prosthesis can function as a perfect replacement as they still lack many of the functions of a natural hand. Prosthesis are limited to a smaller number of gestures, control is not as intuitive as a real hand and is also very limited in feedback to the user such as touch, heat or cold.



Figure 1: A collection of different hand prosthesis. A) Cosmetic prosthesis made from PVC. B) Cosmetic prosthesis made from silicone. C) Body powered hook prosthesis. D) Hand prosthesis with individually moving thumb and two fingers [6-8].

Naturally, creating a modern hand prosthesis involves many challenges, not the least of which is creating a method of control that is both intuitive for the user and accurately interprets the user commands. One approach to achieve this is utilizing electromyography (EMG) to record the activity of the muscles in the lower arm related to hand movement. The loss of the hand does not mean the loss of the signalling pathway of the nervous system and the muscles in the lower arm related to hand movement can still be used even if the hand itself is missing. If the pattern of electrical signals in the remaining muscles of the damaged limb can be read and interpreted correctly as intended gestures a myoelectric control system could allow for intuitive control of the prosthesis and while electromyogram control is a promising field a standard used clinical solution has yet to be created [9-11]. Myoelectric control typically uses surface electrodes to record muscle activity and this approach gives rise to many different factors that affects the performance of an EMG pattern recognition system [12]. During daily use common sources of error are displacement of the electrodes or a change in the conductivity of the skin as a result of humidity caused by sweat or weather conditions. Another possible interference to the classification is the innervation of muscles not related to the intended hand gestures that gives rise to signals which are recorded by the electrodes. This may occur during movements of the arm, when the arm is held in certain positions or when holding a weight or just the weight of the prosthesis itself as additional muscles unrelated to hand movement are activated during these tasks [13-15].

Main goals

This work was done with two main goals in mind. Firstly, can a functional hand prosthesis control system be created using a commercial product such as the Myo™ gesture control armband. If possible, a simple wearable gadget such as the armband could provide an easy method to don and remove the electrodes used for prosthesis control. Creating a control system is also a necessary first step as the second goal involves improvements on an already functional system.

The second goal of this project is to investigate whether the performance of a prosthesis control system can be improved by using the position of the arm in addition to the EMG signals to alleviate the possible interference from arm position, possibly, if the position of the arm is known to the control system errors caused by limb position can be removed or alleviated. To achieve this the Myo™ gesture control armband was used. The armband is, in addition to the surface electrodes, also equipped with three-dimensional gyroscopes and accelerometers. These sensors make it possible for the armband to record additional spatial data which can be used to complement the EMG data recorded by the electrodes. In the project, the pitch and roll recorded by the armband were used.

Introduction

Performing a moment of the hand involves a long signalling pathway originating in the central nervous system and terminating in a muscle, resulting in the contraction of muscle fibres which moves part of the hand via a tendon. In the case of hand amputation, the hand and parts of the tendons may be missing but the muscles of the lower arm and the signalling pathway still remain. A hand prosthesis can therefore be controlled by the same signal used to control the original hand, provided it can be recorded and then properly interpreted. In this project a control system for a hand prosthesis was created by using the Myo™ gesture control armband to record the electrical signals in the muscles of the lower arm. The eight surface electrodes on the armband records the pattern of muscle activity in the lower arm. The control system then classifies the pattern of signals as a certain hand gesture. If the classification of muscle activity happens in

real time and with sufficient accuracy the signals sent to the missing hand can instead be used to control a prosthesis.

A prosthesis control system consists of several steps before the neural signals results in movements of the artificial hand. The following section will give a deeper explanation of the different major steps involved in the process. From the recording of the muscle activity, signal processing and feature extraction to the interpretation and classification of the recorded signal and finally the control system of the potential prosthesis using the recorded data. Figure 2 gives an overview of the major steps. Initially the myoelectric data is recorded by surface electrodes. The raw data must undergo some processing before it can be used for prosthesis control. This involves dividing it into smaller segments and extracting features that will be used to what gesture the signals corresponds to.

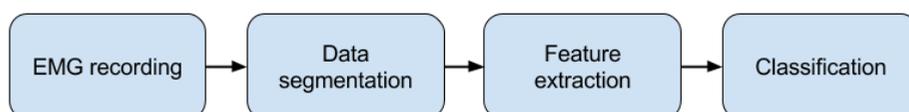


Figure 2: The four major steps involved in translating muscle activity into a form that can be interpreted by a prosthesis. After recording the signals undergo several signal processing steps before they can be used for accurate classification.

The neuromuscular pathway and recording of EMG data

The basic functional part of the neuromuscular system is the motor unit (MU) consisting of a neuron end and a muscle fibre [16]. As the command to use a muscle is initiated in the CNS the signal resulting in a hand movement begins as a depolarization of the neurons connected to the muscles controlling hand movement. The depolarization travels along the neuron axon from the central nervous system to the connection between the neuron and the muscle fibre, the neuromuscular junction (NMJ), illustrated in figure 3.

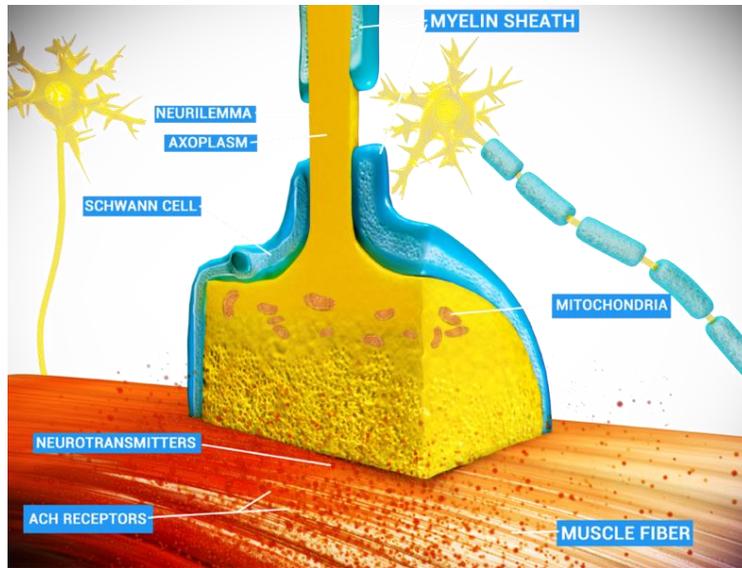


Figure 3: The neuromuscular junction where the axon of the motor neuron connects to the muscle cell, Acetylcholine is released from storage vesicles at the end of the axon as the nerve end depolarizes. Acetylcholine binding to receptors on the muscle cell results in the opening of ion channels that initiate muscle contraction [17].

As the axon end of the neuron depolarizes the neurotransmitter Acetylcholine is released and diffuses over the synaptic cleft into the muscle cell starting the response of the muscle cell resulting in muscle contraction [18]. As the muscle is activated and contracts the electrical activity can be recorded by electrodes placed on the skin above the muscle. Placing several of these electrodes on different parts of the arm makes it possible to measure the activity of the different muscles of the arm in real time. As each movement of the hand is caused by a different pattern of muscle activation each movement can be linked to a pattern of electrical activity as recorded by the electrodes, figure 4 shows the pattern recorded by eight electrodes placed on the lower arm during two hand gestures separated by a period of rest.

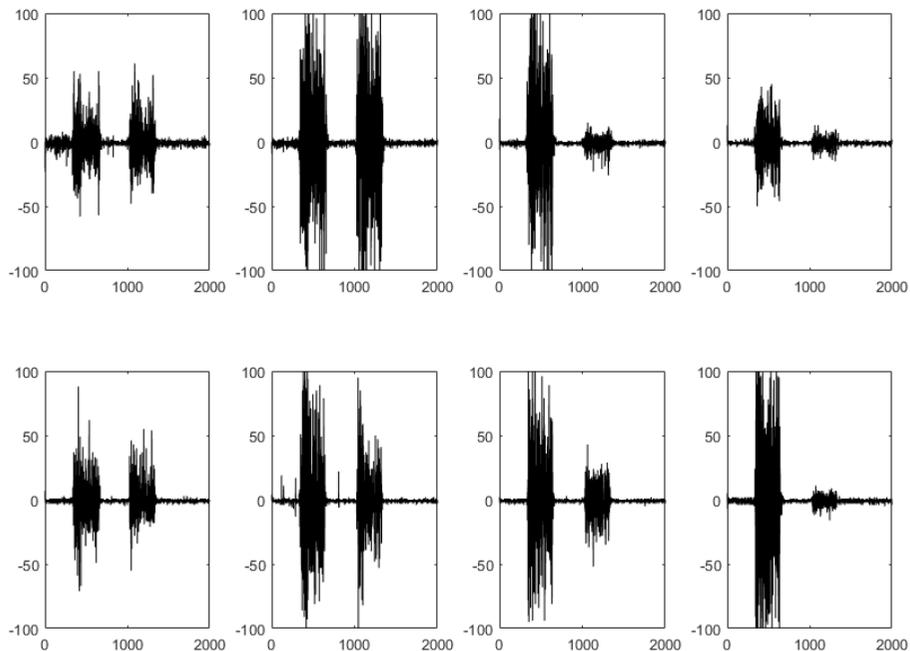


Figure 4: Example of an EMG recording from eight electrodes located on the forearm, time on x-axis and activity on y-axis. The recording shows the different pattern of activity caused by two different gestures separated by periods of rest. When the hand is in rest all channels record a low level of activity. As a gesture is performed the different channels record different levels of activity depending on the gesture.

Signal processing

The raw signal recorded from the electrodes give some information about the activity of the muscles corresponding to each electrode but in this state it is too unwieldy to be useful for classification. This is caused by many different factors such as background noise, electrode displacement, change in conductivity between the skin and electrode or muscle fatigue [19]. Continuous recording of muscle activity produces large volumes of this noisy data which would be unsuitable for direct prosthesis control and several steps of signal processing are necessary. The solution to this is to segment the data, select one or more specific features of the signal, isolate them, and use this processed segment for classification. This produces

smaller, less noisy data sets that are more suitable to be used for classification [20].

A great many different features can be used for classification any can be divided into three categories; time domain, frequency domain and time-scale domain dependant [21] all giving some information about the nature of the signal. A relatively straight forward approach to feature extraction is using the time dependent signal strength as a feature, such as using the mean absolute value defined (MAV) as:

$$MAV = \frac{1}{N} \sum_{n=1}^N |x_n|$$

Where N is the length of the signal and x_n represents the EMG signal in a segment. Using the mean absolute value is a simple way of measuring the level of muscle activity and is a popular feature to use in myoelectric control. This was the feature used for all classification in this project. The mean of a myoelectric signal is close to zero and is not used. Other options include using the root mean square (RMS) which relates to the constant force of non-fatiguing muscle contraction.

$$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^N x_n^2}$$

If the power of the EMG signal is the desired feature the variance (VAR) may be used:

$$VAR = \frac{1}{N-1} \sum_{n=1}^N x_n^2$$

The standard deviation (SD) of the signal relates to the threshold level of muscle activation and can also be used.

$$SD = \sqrt{\frac{1}{N-1} \sum_{n=1}^N (x_n - \bar{x})^2}$$

These features relate to the amplitude of the signal but other aspects of it can also be used. Due to the waveform nature of myoelectric signals the waveform length (WL) can be used, it relates both to amplitude and frequency aspects of the signal.

$$WL = \sum_{n=1}^{N-1} [x_{n+1} - x_n]$$

A feature dependant purely on the frequency of the signal is the zero crossing (ZC), the number of times the signal passes the x-axis.

$$ZC = \sum_{n=1}^{N-1} [sgn(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq threshold]$$

$$sgn(x) = \begin{cases} 1, & \text{if } x \geq threshold \\ 0, & \text{otherwise} \end{cases}$$

Similarly, the zero crossing, the slope sign change (SSC) also relates to the frequency of the signal. SSC is the number of times the slope of the signal shifts between negative and positive in a given time interval.

$$SSC = \sum_{n=2}^{N-1} [f[(x_n - x_{n-1}) \times (x_n - x_{n+1})]]$$

$$f(x) = \begin{cases} 1, & \text{if } x \geq threshold \\ 0, & \text{otherwise} \end{cases}$$

Once one or more desired features has been chosen, they are isolated from the main signal and can be used for classification [22].

Classification

Classification is the process of assigning a set of features a class label. Classification is used in many fields and have countless applications for example, classifying a tumorous cell as benign or malignant or determining the species of a flower. In the case of myoelectric control as done in this project, the features are the MAV values extracted from the recorded EMG signals and the class labels are the different gestures.

There are a great number of different methods that have been developed to classify data in this manner each with their own pros and cons making them suitable for different applications. In order for a method to be able to correctly classify a data point it must first be presented with a set of data consisting of a number of correctly classified data points, called a training set.

A commonly used method is **linear discriminant analysis** (LDA). LDA attempts to find a linear combination of the features and combine them into a single value. The performance of LDA depends on how the features are combined. Ideally the features should be combined in such a way that if the classes are projected onto the axis they are seen as clearly separated tight clusters, see figure 5.

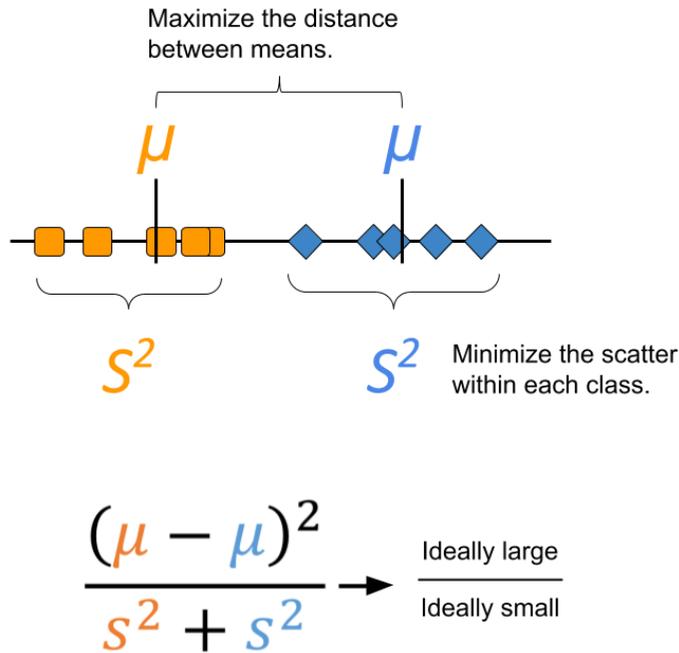


Figure 5: Visualization of LDA. The two classes are identified by two features. The two features are combined and the classes are projected onto this new axis representing the combined features.

LDA is generally suitable when there are many variables and small sample sizes. Comparably, **quadratic discriminant analysis** works similarly but instead separates the classes on a quadratic surface rather than a linear line.

A **Support vector machine** represents the training data as points in space and divides them with a hyperplane positioned as far away as possible from the different points. New points are then easily classified simply by which side of the hyperplane they are positioned. This is easily visualized when dealing with two features and a linear hyperplane, see figure 6. Depending on the maximum-margin hyperplane algorithm used a non-linear hyperplane can also be produced if desired.

Support vector machines are easily optimized but they do not provide a probabilistic confidence value of the classification which may be a drawback in some situations.

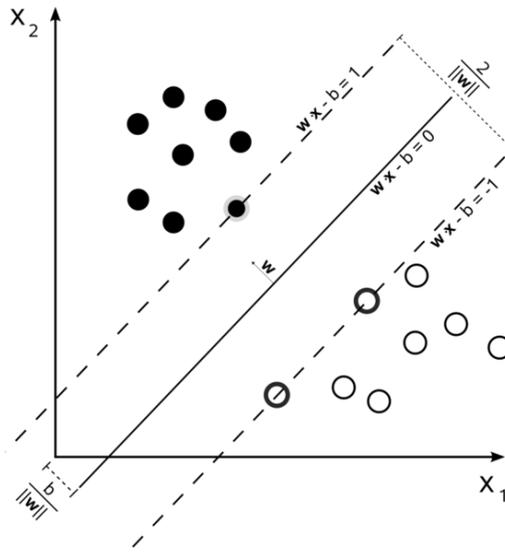


Figure 6: Maximum-margin hyperplane and margins for a support vector machine trained with samples from two classes. Samples on the margin are called the support vectors.

K nearest neighbour is perhaps the most straight-forward classification method. The class of a new data point is determined simply by directly comparing its features to already known data points, See figure 7.

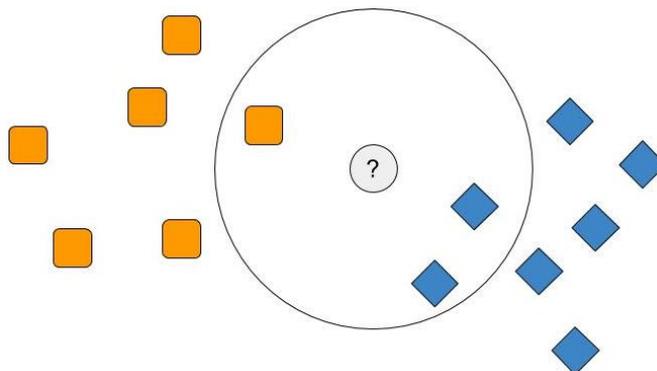


Figure 7: Visualization of the k nearest neighbour method. The unclassified data point is compared to k known classes, in this case $k=3$, and is assigned a class determined by majority vote.

While this method is easy to implement calculations can be slowed by large numbers of data and larger values of k . It also works best when the overlapping of classes is as small as possible.

Another common method for classification is to use an artificial neural network [9, 21]. All classification in this project was done with the use of an artificial neural network and a more in depth explanation of the method follows in the next section.

Regardless of the method used a classifier must be able to keep up with the speed of data recording so that the classification happens in near real-time, the user should not experience a notable delay between command and prosthesis movement. The classifier should also be able to cope well with small variations in the input signal due to the changes that occur in the extracted features after extended use of the armband caused by a number of different reasons such as electrode displacement or muscle fatigue, while a recalibration can be used to correct these errors it is preferable for the user if the system can perform well without frequent recalibration.

Neural networks

An artificial neural network is a program consisting of several nodes connected in a way resembling neurons in a biological brain. These nodes are organized in layers and connect to each other with connections of different weights, positive or negative, much like the neurons of a biological brain is connected via inhibitory or exhibitory synapses. Each node also has an activation function, such as a sigmoid function, acting like the activation threshold in a biological neuron, determining when the signal is passed on to the next nodes. The number of layers can vary but typically a network consists of a minimum of an input layer, an output layer and a layer connecting the two called the hidden layer, illustrated in figure 8. The number of input nodes corresponds to the number of inputs and the output nodes to the possible outputs. In the networks created in this project this means eight inputs when using only EMG signal and ten inputs when using roll and pitch in addition to the EMG. The weight of the connections and the activation function of the nodes define the flow of information through the network and determines the output to an input signal.

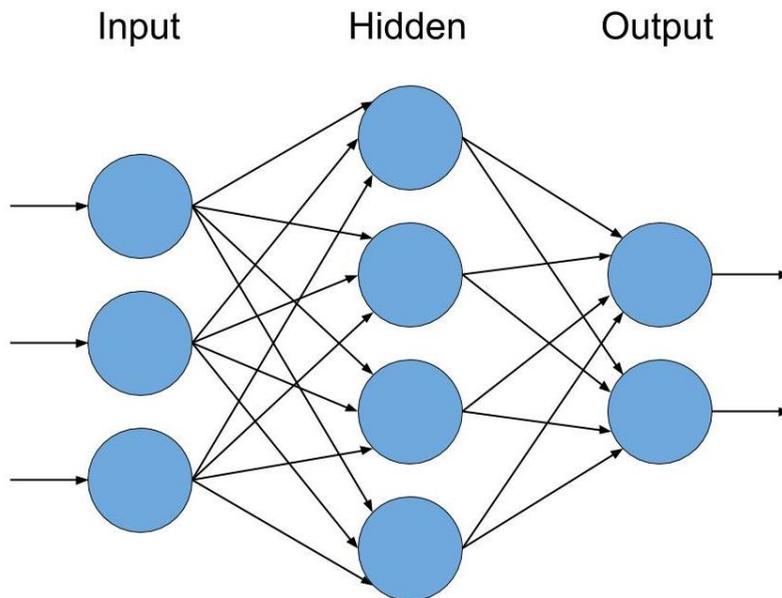


Figure 8: Visualization of a simple artificial neural network consisting of three layers.

A network is created using a set of input data with corresponding output data. The data is divided into three sets used for training, validation and testing respectively with a majority of the data being used for training. The training set determines the weights between the nodes as the network is created. A possible mistake when creating a network is overtraining which causing overfitting by the networks functions making it unsuitable for handling unknown inputs, see figure 9. To prevent this the validation set is used. The validation set does not affect the weights of the system but acts as an indicator of when it is time to stop the training. If additional training increases the accuracy of the training data set but the accuracy of the validation set decreases or remains the same the system has started overfitting and training should cease as overfitting would greatly reduce the networks performance when faced with input data not from the training set.

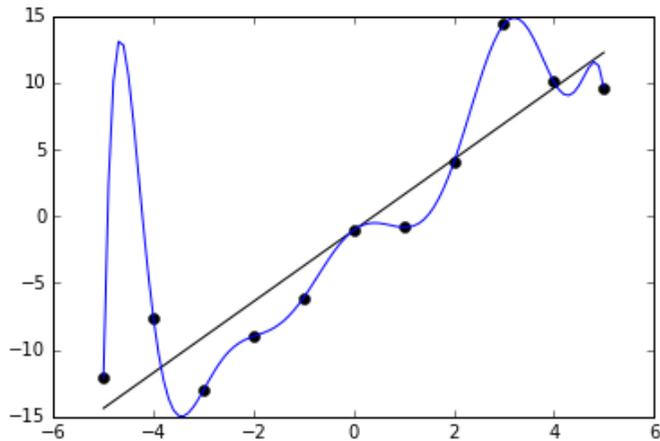


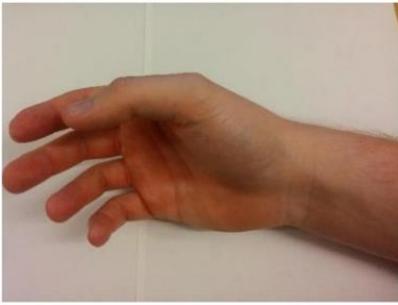
Figure 9: Example of overfitting. The blue line is the results of a function overfitted to the data points, while this model agrees with all known data points it is useless in predicting any new points. The black line, while not fitting any of the point perfectly, is a much better model in this case as it more accurately shows the trend in the data and can be used to predict new data points. Similarly a neural network overfitted to the training set data will perform poorly when encountering new inputs [23].

Finally, the testing set is used to estimate the accuracy of the network. This data set is new to the network and tests its performance when faced with unknown data, giving an estimation of the networks performance.

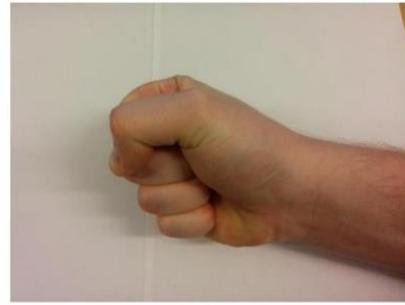
Creating the prosthesis control program

The control system created in this project involves the four major steps described in the introduction, however several additional steps and methods were added in order to improve performance and reliability as well as making the program more intuitive for the user. This section describes the creation process of the program, the steps involved and the equipment used.

In any gesture control system, the choice of which gestures to use is an important one. Using a few distinctly different gestures would make it easier for the program to distinguish between them but would limit the usability of the prosthesis. Ideally the prosthesis and control system would be able to recognize and perform the same movements as a regular hand but such a system is not possible with current technology. Instead a balance must be found between system accuracy and number of useful gestures [24]. Another point to consider is how intuitive the gesture is for the user, if a gesture is easily recognized by the program but feels awkward or unnatural to perform it may not be a good choice. Following these criteria eight gestures were chosen, shown in figure 10.



1. Rest



2. Fist



3. Open



4. Folded outwards



5. Folded inwards



6. Point



7. Pinch



8. Key grip

Figure 10: The eight gestures that were chosen for the project.

These gestures were chosen as they are all distinguishable from each other resemble useful everyday gestures. An argument could be made that gesture 4 and 5 are not very useful, however, the gestures of the prosthesis does not necessarily have to match those of the user, for example, gesture 5 could translate to a more useful cupping gesture while still being intuitive. Similarly, gesture 6 is not what most people would do if asked to point, the motion is exaggerated for easier classification.

The Myo™ Armband

All recording of EMG data performed during this work was done using the Myo™ gesture control armband, shown in figure 11, developed and sold by Thalmic Labs Inc. The armband is intended to be used for gesture control of common programs such as Spotify, PowerPoint presentations and a variety of media player. To fulfil these functions, the armband is able to recognise four gestures using its own classification system. This accompanying classification software was not used in this project and the armband served solely as a recording device.



Figure 11: The Myo™ armband. The eight electrodes are connected via flexible sections that can be stiffened by attaching clips, making the armband able to snugly fit around the lower arm.

The armband is equipped with eight electrodes, a three-axis gyroscope, a three-axis accelerometer and a three-axis magnetometer. This setup of sensors allows the armband to determine and report its position in a three-dimensional space in addition to the EMG data. The armband contains an ARM Cortex M4 Processor and a rechargeable lithium ion battery allowing it to be used completely wirelessly, using a Bluetooth connection to either a Windows PC or MAC. Feedback is given to the user via LEDs and vibration pulses of varying length [25].

To ensure maximum signals strength the armband is placed around the thickest part of the upper lower arm.

Feature selection and extraction

The armband is capable of recording EMG data at 200 Hz but is limited to 50 Hz when also recording positional data such as pitch, yaw and roll. The feature chosen for classification was the mean absolute value of the EMG signal, in tests involving positional data pitch and roll of the armband were used as features in addition to the EMG. To calculate the mean average, the stream of recorded EMG signals was segmented, as is often the case, the choice of segment length is a choice between speed and accuracy. A longer segment could provide a better mean value and is more resistant to spikes or dips in the signal but using longer segments would also reduce the systems response time [26]. To circumvent this to some degree the segments can be overlapped, see figure 12. When using overlapping longer segments can be used while having a smaller impact on system response time.

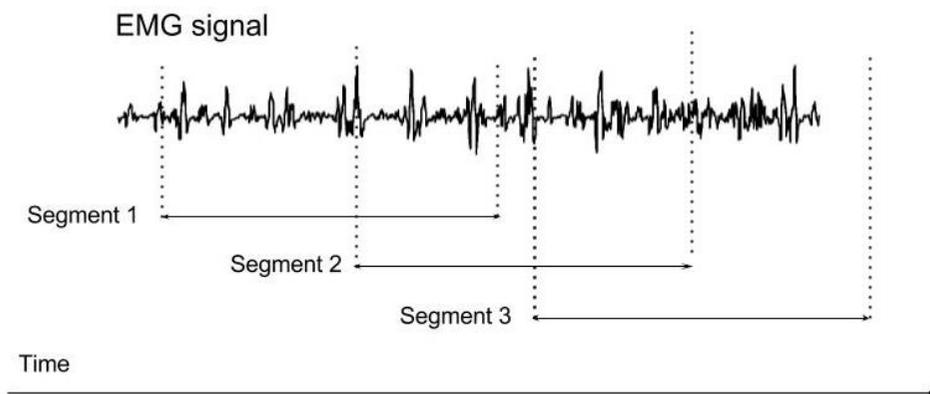


Figure 12: Visualization of overlapping data segmentation. The continuous stream of EMG data is being divided into smaller segments that will be used for feature extraction.

Following the findings of L Smith et al. [26] in a work determining the optimal window length and spacing during myoelectric control, the program uses segments consisting of 30 data points corresponding to a segment length of 150ms. The segments overlap by five data points which introduces a delay of 25ms to the system as new data is recorded before the next segment is sent to classification.

Classification

All classification in the system was done using an artificial neural network created for each user. All neural networks were created in MatLab using the nprtool interface shown in figure 13 and 14.

Using the MyoTM armband a large set of data was recorded as the user performed each gesture twice separated by a period of rest. The recorded training data with corresponding class labels are fed to the network training tool and randomly divided into the training, validation and test set consisting of 70%, 15%, and 15% of the total set respectively following the default settings of the program. The created network consists of eight input nodes, one for each electrode, a hidden layer consisting of ten nodes and an output layer consisting of eight nodes, one for each gesture. The number

of inputs and output nodes naturally corresponds to the number of inputs and outputs used while the number of nodes in the hidden layer can be customized. Ten was found to be a suitable number as adding more nodes did not cause any significant improvement in performance.

Using the training data, the network goes through many iterations adjusting the weights between the nodes and improving the classification accuracy of the training set. This accuracy is continuously compared to the accuracy of the validation set. When the accuracy of the validation set stops improving with further iterations the training stops to prevent overfitting.

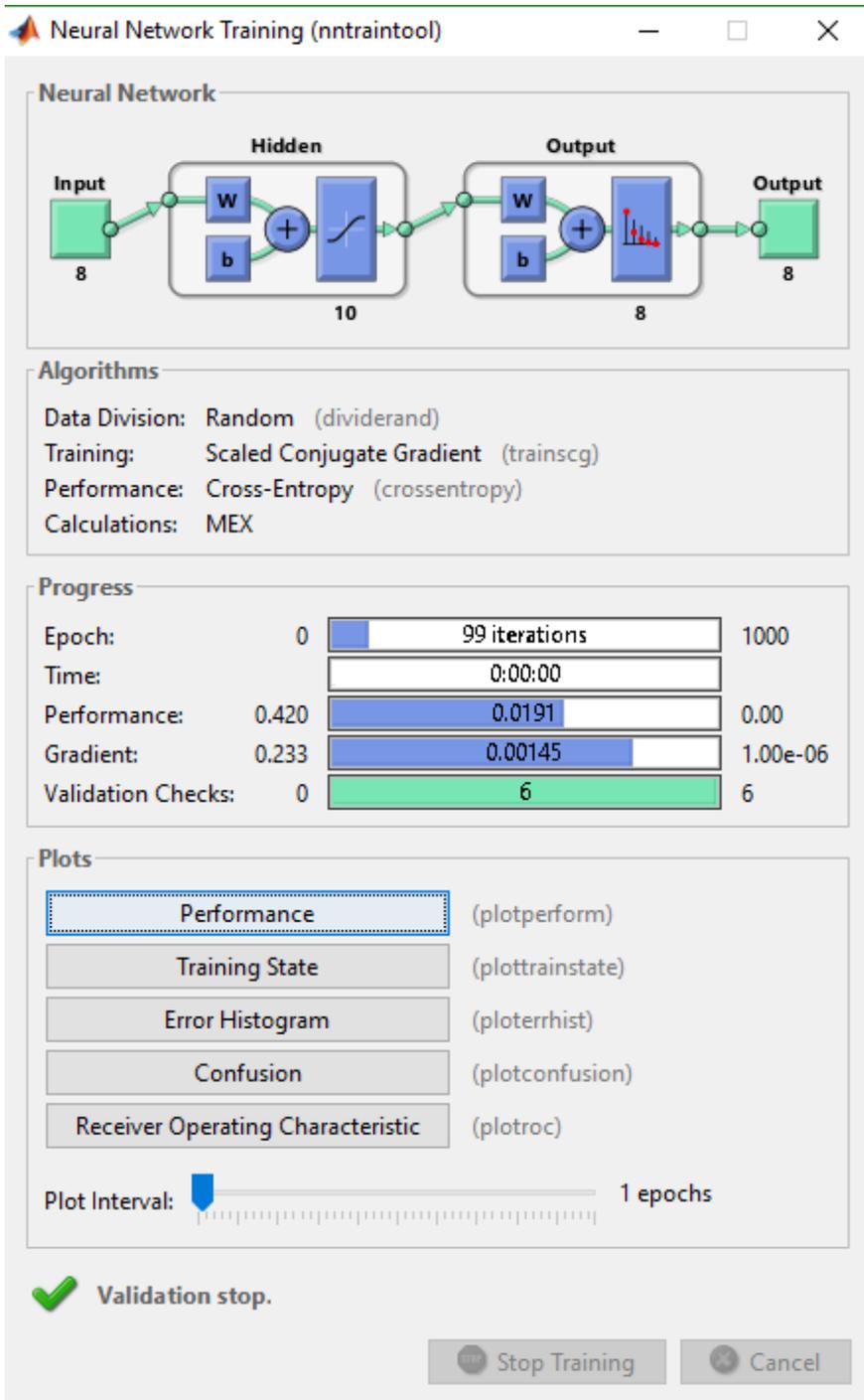


Figure 13: The nprtool MatLab interface. Training of this network has stopped after 99 iterations as the accuracy on the validation set has stopped improving.

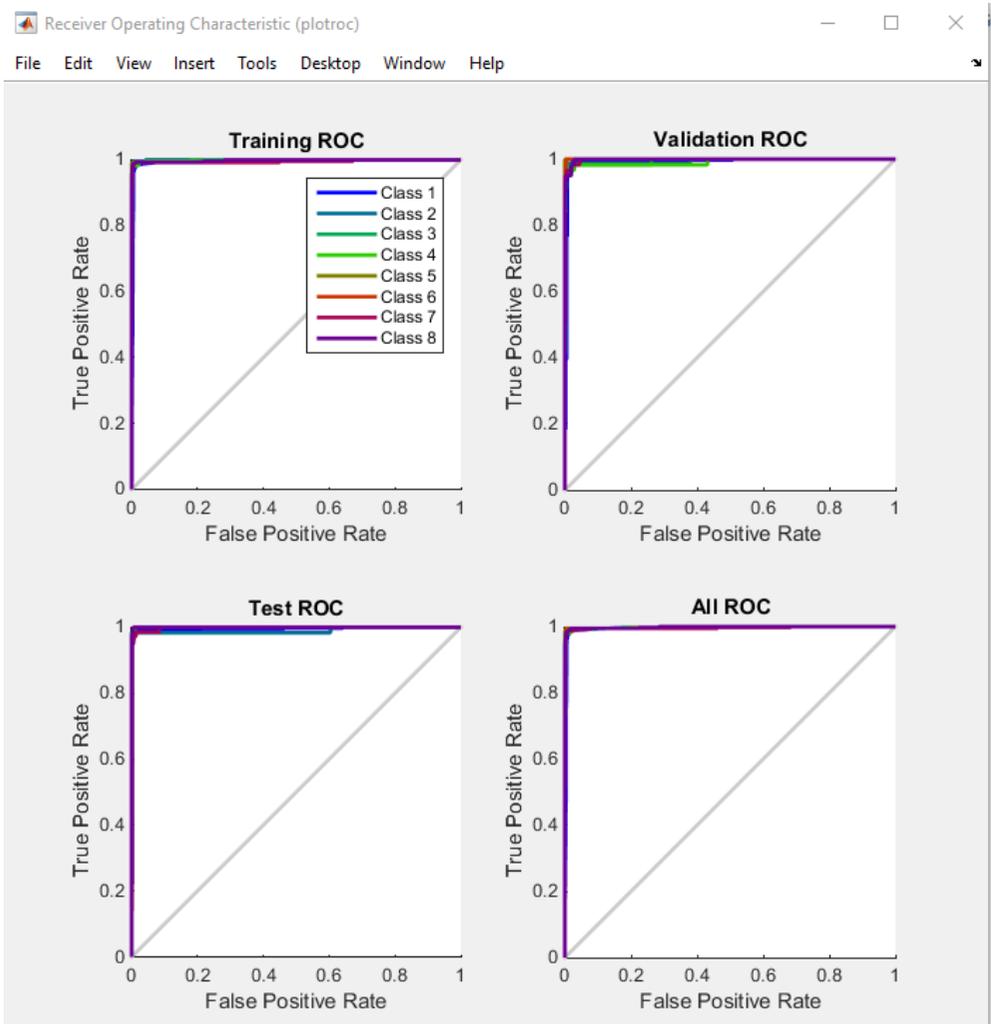


Figure 14: Receiver operating characteristic plots created after training of the network to give an estimations of the networks performance. This particular network shows promising results as the ROC curve has an almost ideal shape.

After completed training the network is saved as a MatLab function by the network training program and can now be used to classify new inputs.

Producing class label as the network is presented with a new feature segment involves two steps. Firstly, as the network receives input in the form of the features extracted from the EMG signal in the previous step each output node produces a value between zero and one and the signal is

classified as the gesture that received an output value of >0.95 . If this requirement is not met i.e. for all classifications were no output node received a value greater than 0.95 the previous class label is returned. This requirement on the output creates a more rigid system as the class label is only changed if the system is very certain of the classification, reducing the amount of misclassifications at the cost of response time.

This classification is then added to a list consisting of the five latest classifications and the final class label is the gesture that appears the most in this list. As the next feature segment is classified the list is updated as the oldest value is removed and the latest added. This system sacrifices some response time as a gesture must be classified at least three times to achieve majority and affect the class label but also makes the system more robust as it lessens the impact of singular misclassifications.

Additional control

At this stage the program records and classifies the EMG data in near real time. This is enough to control a prosthesis but there is room for several improvements. For example; the system cannot perform movements at different speeds or grip strengths and to make the prosthesis remain in a certain gesture the command to do the desired gesture must be sent continuously. All this adds up to a control system that is functional but not very convenient in daily use.

A way to utilize this stream of data to create a more user friendly system is to implement a finite element machine to control the prosthesis. A finite state machine is a system consisting of a number of predetermined states, only one state is active at the time and switches between states is decided by the input. An example of a simple state machine is a system with two states, on and off, using a sine function as input and the trigger to go from the off state to the on state is the input being larger than zero and vice versa, see figure 15. A system designed this way would continuously switch between the on and off state as the sine function changes value between positive and negative.

Input: $y = \sin(x)$

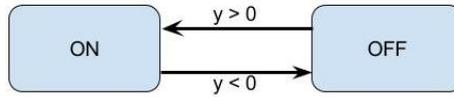


Figure 15: Example of a simple finite state machine consisting of two states. The machine continuously switches between the on and off state as the input signal changes value.

The state machine used by the control system consists of eight states, one for each gesture, and uses the class provided by the neural network as input. The system was designed to use rest as the default state, performing a different gesture while in the default state switches state to new gesture, with the exception of gesture 3 which was used to return to the rest state regardless of current state. Figure 16 provides a visualization of the finite state machine, showing how the different states relates to each other and how the input determines the change between states.

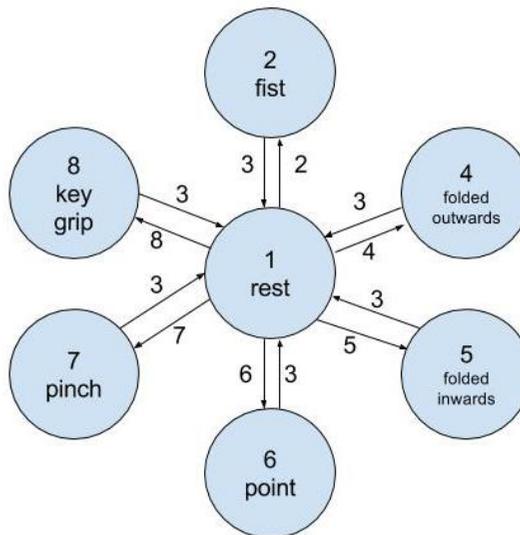


Figure 16: Visualization of the finite state machine used by the control system. The machine consists of seven states and the input signal is the class label provided by the classifier. At rest performing a gesture will switch to the corresponding state and remain there until the command to return to the rest state is given.

This setup allows the user to let the prosthesis remain in a certain position without having to continuously flex the muscles of the lower arm as relaxing the muscles never switches states. It also reduced the risk of the prosthesis suddenly performing unintended movements resulting in a more reliable and user friendly system.

Another factor that could improve user experience and add additional control is the ability to choose the speed at which the prosthesis performs the gestures [27]. By enabling the prosthesis to perform gestures at different speed or stop a gesture before it is completed and remain in that position a much higher degree of fine control would be reached. This can be achieved by using proportional control. The sum of the MAV from the eight electrodes can be normalized and used to decide motor speed in the prosthesis. This creates a control system where straining the lower arm harder when doing a certain gesture makes the prosthesis perform the correlating movement faster.

Results

The testing was divided into two major parts, firstly the possible improvement to classification accuracy by using positional data in addition to the EMG signals were investigated.

Secondly the performance of the final version of the control system was tested by nine users, evaluating the accuracy and response time of the control system when used by a variety of different users with no experience of the system.

Evaluating the effect of position on classification accuracy

To test the impact of using positional data on classification accuracy two sets of training data were prepared. Both using the eight gestures and recording both EMG and positional data. The first set was recorded during a small waving movement of the arm and the second during a larger circular motion of the arm, see figure 17. With these two sets of data four neural networks were created, two using the pitch and roll of the armband in

addition to the EMG data as input in the training set and two using only EMG as input.

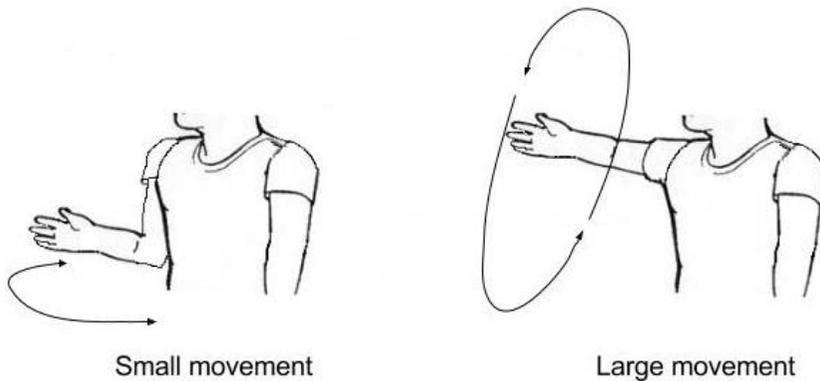


Figure 17: The small and large movement of the arm used when testing classification accuracy.

The four networks trained with the four training sets were tested individually. The accuracy test was done by performing the eight gestures after each other, recording 100 data points per gesture, the 800 data points are then fed to the classifier and the percentage of correct classifications was calculated by comparing the classifiers results to the intended sequence of gestures. The mean accuracy was calculated from three recordings. This test was done with all networks, once with no movement of the arm and once with the small or large movement the network had been trained with, results shown in tables 1-3.

Networks trained during small movement				
input	EMG only		EMG and position	
Arm movement during test	no movement	movement	no movement	movement
Accuracy %	82,3	82,0	89,3	83,3

Table 1: Results using the two networks made from the training set recorded during small movement of the arm.

Networks trained during large movement				
input	EMG only		EMG and position	
Arm movement during test	no movement	movement	no movement	movement
Accuracy %	80,7	81,3	82,7	75,3

Table 2: Results using the two networks made from the training set recorded during large movement of the arm.

An additional test was performed using the two network trained with the data from the large movement but this time the movement of the arm during testing was completely different than that from training, presenting condition the networks were not trained for.

input	EMG and position	EMG only
Accuracy %	34,0	83,0

Table 3: Results from testing the two networks trained during large movements with a movement of the arm unfamiliar to the system.

Evaluating system performance

The final version of the software was evaluated by two criteria; classification accuracy and response time. The system was tested by nine different users. During evaluation the finite element machine addition was not used. Testing procedure began with the training of a neural network calibrated to each user. Users performed each gesture in order separated by a period of rest to record the EMG data corresponding to each gesture. This data was then divided into a training, validation and test set using 70%, 15% and 15% of the total set respectively. Using this data an artificial neural network was created for each user.

The result of the test data performance evaluation is presented as a confusion matrix in figure 18. The number in each coloured square represents the percentage of the total test data set in each target/output combination. As a period of rest was recorded between each gesture a perfect confusion matrix would have 50% of the data set in the upper-left corner, ~7.1% in the remaining green squares and zero in all red squares. The horizontal light grey section shows the percentage of each input that was correctly classified and the vertical light grey section shows the percentage of each class label that was correct. The average accuracy is given in the lower right corner.

After creation of the network the users were given a few minutes to get accustomed to the program. During this practice stage classification of gestures was done in real time and shown to the user as feedback but no data was recorded.

To test the accuracy of the running system the users were asked to perform the eight gestures in order while recording the classification. The recorded classification was then compared to the intended gestures and the accuracy of the classification calculated. This was repeated three times for each user, results presented in figure 19.

Offline test:

Output Class	1	48.4	0.1	0.3	0.2	0.1	0.3	0.3	0.4	96.8
	2	0.1	7	0	0	0	0.1	0	0.3	93.3
	3	0.3	0	6.4	0.2	0	0.1	0	0.1	91.0
	4	0.2	0	0.1	5.9	0	0.5	0.2	0.1	85.2
	5	0.2	0	0	0	6.7	0.1	0	0	95.5
	6	0.4	0	0.2	0.7	0	6.4	0.3	0	80.6
	7	0.2	0.1	0.1	0.2	0	0.4	5.8	0.3	85
	8	0.2	0.1	0.1	0	0	0	0.1	6.2	91.3
			97	94.9	90.1	83.8	98.7	81.4	86.2	85.4
		3	5.1	8.9	16.2	1.3	18.6	13.8	14.6	7.3
		1	2	3	4	5	6	7	8	
		Target Class								

Figure 18: Confusion plot produced by the test data set recorded during neural network training.

Online test:

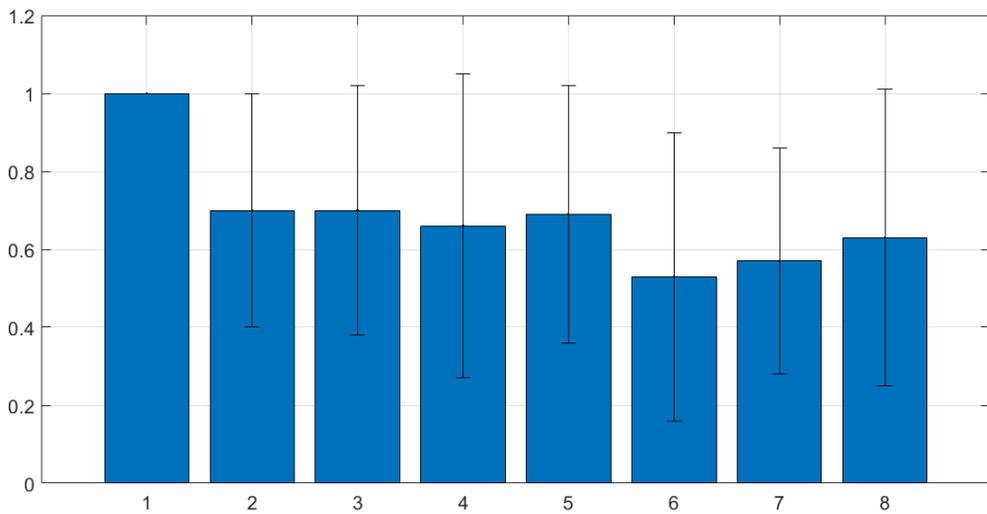


Figure 19: Results of the online test performed by the nine users. Bars showing the fraction of correct classifications for each gesture and the standard deviation for that gesture.

Finally, the response time of the system tested. Following a similar approach to Guanglin Li *et al.* [28] system response time was evaluated by two criteria: motion selection time and motion completion time. Motion selection time is defined as the time from onset of motion to the first correct classification of the movement by the system. See figure 20, while the hand is in rest the recorded EMG activity is low and a baseline activity can be determined, marked by the horizontal line in the graph. As a gesture is performed, the EMG activity increases and the delay from movement onset to the new gesture being classified can be calculated as the sampling rate of the system is known.

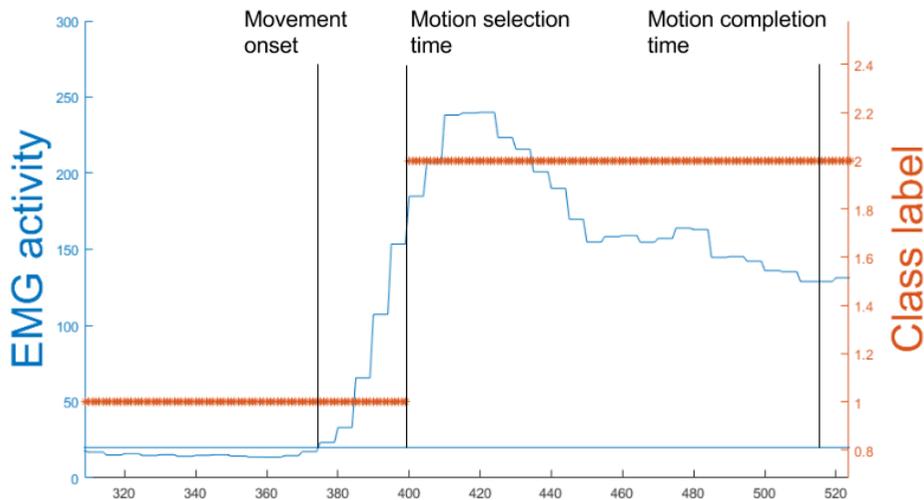


Figure 20: Graph created during response time testing showing both EMG activity and class label, in this case, a change from rest to gesture 2 (fist). Movement onset is defined as the point where the EMG activity raises over the rest activity, marked by the horizontal straight line. The time between movement onset and the first correct classification marks the motion selection time. The motion completion time is defined as correct classification corresponding to one second.

Motion completion time is the time it takes for the system to complete the intended motion defined as correct classifications corresponding to 1 second. In addition to the unavoidable delay in the system as a result of the signal processing and computational steps the motion selection time and

motion completion time are also increased by misclassifications, see figure 21.

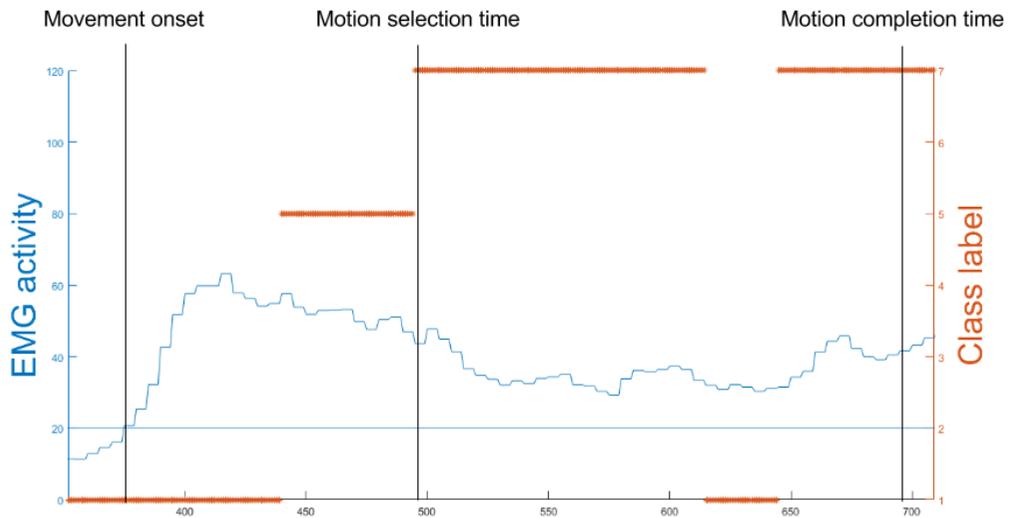


Figure 21: Graph recorded during change from rest to gesture 7 (pinch grip). In this recording both the motion selection time and motion completion time are increased by misclassifications. After movement onset the system incorrectly classifies the movement as gesture 5 (folded inwards) before the correct classification is made. The motion completion time is also lengthened by a section incorrectly classified as rest.

Due to the difficulties with reliably performing each gesture the different users had the response time test was only done on one user. Each gesture was performed five times from a period of rest and held until the motion completion time could be determined while the EMG activity and class labels were continuously recorded. Using the resulting graphs, the mean motion detection and motion completion time was calculated, presented in table 4. Note that a response time for gesture 1, rest, cannot be calculated using this method.

gesture	2	3	4	5	6	7	8
Motion selection time (ms)	100 ± 18	120 ± 21	135 ± 65	255 ± 195	135 ± 29	280 ± 191	55 ± 11
Motion completion time (s)	1 ± 0	1 ± 0	1,09 ± 0,129	1,07 ± 0,157	1 ± 0	1,07 ± 0,095	1 ± 0

Table 4: Results from the motion selection and completion time test.

Discussion

As demonstrated by the high accuracy given in the offline test, the use of the Myo™ armband as the recorder of EMG signals proved successful in this project. Showing that a commercially available product with a simple radial distribution of electrodes it capable of distinguishing between, at the very least, the eight gestures used in the project. However, it should be noted that no long term tests where the armband was worn for a full day of use was performed. It is likely that the performance would degrade during extended use by factors previously mentioned such as electrode displacement.

The online test introduces the human element into the testing, with the exception of gesture 1, rest, the accuracy of the system differed widely between the different users in the online test. As reflected in the large standard deviation in gestures 2-8. The accuracy of each gesture was generally either poor, <20%, or good, >80%, with few gestures having a more average accuracy. While most user had one or more gesture performing poorly and the others better it was different gestures for different users, resulting in the large standard deviation. For example, a common problem was misclassification of gesture 3 as gesture 4 or vice versa. Resulting in some user having very good accuracy in gesture 3 but low in gesture 4 and others having the exact opposite.

This is most likely caused by user inexperience with the system, without a longer training period to get used to use the system many users found it difficult to reliably quickly switch to a specific gesture, this quickly leads to

a large percentage of incorrect classifications as each gesture was only recorded for 100 data points, 0.5 seconds, during the accuracy test. It should be noted that the user with greater experience with the program (the author) achieved >80% accuracy for all gestures, reaching the same levels of accuracy as the offline test. This was also achieved by one of the other users. The great difference could also be explained by the short recording time for each gesture, choosing a longer recording time would result in a higher calculated accuracy as a greater portion of the data would be recorded after the user has found the correct gesture. That said, the system should be able to quickly change between gestures and shorter recording times creating a stricter test may better represent what is expected of the system in daily use [28-30].

To avoid a noticeable delay by the user the system response time should at the very least be no greater than 300ms. Preferably lower, in the 100ms range [21].

This level of responsiveness was achieved by some gestures while others took significantly longer, motion selection time varies between 55 and 280ms in the two most extreme cases. The delay is in a large part determined by the way the system is constructed. Caused by computing steps and overlapping of segments during recording. This kind of delay is to a certain degree unavoidable but possible to reduce by using a more efficient program or shorter segment overlap.

The delay caused by the system should however affect all gestures equally and cannot be the reason such a large variance in response time is observed between the different gestures. Instead this delay is most likely a result of how strict the system is when applying class labels and user error. While a strict system reduces the amount of misclassification it also demands a more precise input from the user. While lowering the classification strictness could improve this response time it is also possible that it could be reduced with more user experience as the user gains a more intuitive feel for the system. Another approach would be a change to the training routine, if the gesture is performed less strictly during training the system should correctly classify a larger variance in input, provided it is not too similar to a different gesture.

At several points in the system the choice is made between response time and accuracy, for example the requirement that the output node of the neural network must have a value of at least 0.95 before creating a new class label. This rigidity of the system is reflected in the observed motion completion time which was close to one second for all gesture with very little variation. By the way the motion completion time was defined it is natural that a system that is “unwilling” to quickly change class labels would produce short motion completions times.

Using the positional data in addition to the EMG to improve system accuracy proved a failure. In cases when the arm was moved in a similar way to that during training it resulted in no significant improvement of accuracy. When presented with an arm movement not performed during training the accuracy was significantly lowered.

This is a result of using the pitch and roll directly as inputs to the neural network which may have been a poor approach as it necessitates the arm being moved in all positions expected of daily use during training of the network. Not doing so results in the network often receiving input values not present in the training set, significantly lowering performance. A training routine going through all the expected arm positions during daily use could be created but as this application of positional data had no beneficial effect on classification accuracy it is probably better to choose another approach to this problem altogether.

Conclusion

Myoelectric prosthesis control shows great promise in reducing the negative impacts the loss of a limb can have. While the technology is still far from perfectly replicating a biological limb prosthetics are capable of significantly improve the quality of life for people who are affected.

This project aimed to create a functional myoelectric control system and investigate how the effects of limb position on system accuracy can be alleviated. While a functional myoelectric control system for a hand prosthesis using the Myo™ armband was created, attempting to use the

positional data provided by the armband did not result in any increase in accuracy compared to using only the EMG data.

However, this project covered only one approach of utilizing the positional data and showed that the Myo™ armband can be used for prosthesis control. The work done during this project could be expanded upon in different directions in future work. Much can be done to streamline the system and improve the training routine as well as exploring new ways to use the positional data made available by the armband.

References

1. Burger, H., T. Maver, and Č. Marinček, *Partial hand amputation and work*. Disability and Rehabilitation, 2007. **29**(17): p. 1317-1321.
2. Ziegler-Graham, K., et al., *Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050*. Archives of Physical Medicine and Rehabilitation, 2008. **89**(3): p. 422-429.
3. Atroshi, I. and H.E. Rosberg, *Epidemiology of amputations and severe injuries of the hand*. Hand clinics, 2001. **17**(3): p. 343-50, vii.
4. Belter, J.T., et al., *Mechanical design and performance specifications of anthropomorphic prosthetic hands: A review*.
5. Yang, J., et al., *A multi-fingered hand prosthesis*. Mechanism and Machine Theory, 2004. **39**(6): p. 555-581.
6. *Body-powered hand prosthesis*. [cited 2016 26-10]; Available from: <http://www.medicalexpo.com/prod/fillauer/product-74954-466476.html>.
7. *Male APRL Voluntary Closing Hand*. [cited 2016 26-10]; Available from: <http://fillauer.com/Upper-Extremity-Prosthetics/body-powered-systems/hands-and-gloves/male-hands/male-APRL-voluntary-closing-hand.html>.
8. *Comparison of mechanical properties of silicone and PVC (polyvinylchloride) cosmetic gloves for articulating hand prostheses*. [cited 2016 26-10]; Available from: <http://www.rehab.research.va.gov/jour/2013/505/page723.html>.
9. Scheme, E. and K. Englehart, *Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use*. Journal of Rehabilitation Research & Development, 2011. **48**(6): p. 643-659.
10. Parker, P., K. Englehart, and B. Hudgins, *Myoelectric signal processing for control of powered limb prostheses*. Journal of Electromyography and Kinesiology, 2006. **16**(6): p. 541-548.
11. Zecca, M., et al., *Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal*. 2002. **30**(4-6): p. 459-485.
12. Castellini, C. and P. Smagt, *Surface EMG in advanced hand prosthetics*. Biological Cybernetics, 2008. **100**(1): p. 35-47.

13. Fougner, A., et al., *Resolving the Limb Position Effect in Myoelectric Pattern Recognition*. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2011. **19**(6): p. 644-651.
14. Scheme, E.J., K.B. Englehart, and B.S. Hudgins, *Selective Classification for Improved Robustness of Myoelectric Control Under Nonideal Conditions*. IEEE Transactions on Biomedical Engineering, 2011. **58**(6): p. 1698-1705.
15. Cipriani, C., et al., *The Effects of Weight and Inertia of the Prosthesis on the Sensitivity of Electromyographic Pattern Recognition in Relax State*. JPO: Journal of Prosthetics and Orthotics, 2012. **24**(2): p. 86-92.
16. Gazzoni, M., D. Farina, and R. Merletti, *A new method for the extraction and classification of single motor unit action potentials from surface EMG signals*. Journal of Neuroscience Methods, 2004. **136**(2): p. 165-177.
17. Jana, D., *Neuromuscular junction*. Doctor Jana free medical stuff.
18. Wu, H., W.C. Xiong, and L. Mei, *To build a synapse: signaling pathways in neuromuscular junction assembly*. Development, 2010. **137**(7): p. 1017-1033.
19. Farina, D., R. Merletti, and R.M. Enoka, *The extraction of neural strategies from the surface EMG*. Journal of Applied Physiology, 2004. **96**(4): p. 1486-1495.
20. Reaz, M.B.I., M.S. Hussain, and F. Mohd-Yasin, *Techniques of EMG signal analysis: detection, processing, classification and applications*. Biological Procedures Online. **8**(1): p. 11-35.
21. Asghari Oskoei, M. and H. Hu, *Myoelectric control systems—A survey*. Biomedical Signal Processing and Control, 2007. **2**(4): p. 275-294.
22. Ahsan, M.R., M.I. Ibrahimy, and O.O. Khalifa. *Electromyography (EMG) signal based hand gesture recognition using artificial neural network (ANN)*. in *Mechatronics (ICOM), 2011 4th International Conference On*. 2011.
23. Ghiles, *Overfitted data*.
24. Castro, M.C.F., S.P. Arjunan, and D.K. Kumar, *Selection of suitable hand gestures for reliable myoelectric human computer interface*. BioMedical Engineering OnLine, 2015. **14**(1): p. 1-11.
25. *MYO armband technical specifications*. [cited 2016 13-07]; Available from: <https://www.myo.com/techspecs>.

26. Smith, L.H., et al., *Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay*. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2011. **19**(2): p. 186-192.
27. Simon, A.M., et al., *A Decision-Based Velocity Ramp for Minimizing the Effect of Misclassifications During Real-Time Pattern Recognition Control*. IEEE Transactions on Biomedical Engineering, 2011. **58**(8): p. 2360-2368.
28. Li, G., A.E. Schultz, and T.A. Kuiken, *Quantifying Pattern Recognition—Based Myoelectric Control of Multifunctional Transradial Prostheses*. IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society, 2010. **18**(2): p. 185-192.
29. Ortiz-Catalan, M., et al., *Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms*. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2014. **22**(4): p. 756-764.
30. Simon, A.M., et al., *The Target Achievement Control Test: Evaluating real-time myoelectric pattern recognition control of a multifunctional upper-limb prosthesis*. Journal of rehabilitation research and development, 2011. **48**(6): p. 619-627.

Appendix

Presented in this section is the MatLab code written during this project as well as a summary of the project in the form of a popular science article written in Swedish aimed at an audience unfamiliar with the field of myoelectric control.

Myoelektrisk kontroll av handprotes

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Handledare: Christian Antfolk, Examinator: Frida Sandberg

Populärvetenskaplig sammanfattning av arbetet: Robust control of hand prosthesis using electromyogram, accelerometers and gyros.

Att förlora en hand är en stor förlust och även om allt mer avancerades proteser tillverkas är de fortfarande långt ifrån att prestera lika bra som en riktig hand. För att kunna styra handproteser på ett intuitivt sätt används myoelektrisk kontroll. En metod där man spelar in kroppen muskelsignaler och översätter dem till signaler som kan styra t.ex. en robohand.

Att röra på handen är något vi gör varje dag utan eftertanke men varje liten rörelse är resultatet av en lång signalkedja med ursprung i hjärnan. Om du vill knyta handen skickas först en nervsignal ut från hjärnan, denna signal färdas via långa nervtrådar ut i armen och når muskler i handen och underarmen. När musklerna nås av signalen drar de ihop sig och drar i de senor som binder samman muskler och skelett och handen knyts. Det finns en mängd olika muskler som påverkar handen och genom att aktivera dem till olika grad kan vi utföra alla de gester vi gör med våra händer varje dag.

Detta innebär att även om man förlorat handen i t.ex. en olycka eller sjukdom finns en stor del av system som styr handen fortfarande kvar. Man kan skicka muskelsignaler som påverkar underarmens muskler men då handen saknas tar det stopp här. Dessa signaler kan ändå komma till nytta, när en muskel drar ihop sig skapas det en liten elektrisk signal som kan spelas in av en elektrod i närheten. Genom att fästa flera elektroder kring de olika musklerna i armen kan man tolka muskelsignalerna som skickas och använda dessa som instruktioner för hur en konstgjord hand skall röra sig. Om detta lyckas skulle man kunna skapa en konstgjord hand som styrs lika naturligt som en riktig då man använder sig av exakt samma signaler som innan handen förlorades. Så pass avancerade proteser finns ännu inte idag, de är istället begränsade till ett mindre antal gester och det är inte alltid system tolkar signalerna rätt.

Detta projekt delades upp i två huvuddelar: först och främst skapades ett enkelt styrsystem som

med hjälp av elektroder kring underarmen kan känna igen åtta olika gester. Ett vanligt problem med denna typ av styrsystem är att de får svårare att tolka nervsignalerna när rör på armen eftersom elektroderna som ligger på huden rör sig i förhållande till musklerna under huden när armen hålls i olika positioner.

Som en andra del av projektet undersöktes därför ifall styrsystemet kunde förbättras om man använder sig av mer data än enbart muskelsignalerna.

För att uppnå detta användes Myo™ gesture control armband. Armbandet består av åtta elektroder men är också utrustat med sensorer som låter armbandet känna av hur det är orienterat i rummet. Tanken är att denna extra data skall kunna användas för minska problem som uppstår när armen rör sig mellan olika positioner.



Figur 1: Armbandet som användes till projektet. Myo gesture control armband, utvecklat av Thalmic Labs.

Projektet slutade i blandade resultat. Första delmomentet uppnåddes då Myo armbandet kunde användas till att skapa ett fungerande system som kände igen åtta olika gester. Systemet testades på nio olika användare och utvärderades efter träffsäkerhet och responstid. Träffsäkerheten var i bästa fall på över 80 % för alla gester, detta uppnåddes dock bara av en användare. Responstiden i systemet varierade kraftigt mellan de olika gesterna, målet var att komma under 100ms vilket enbart uppnåddes av två gester.

Delmoment två uppnåddes inte. Under försök där den extra informationen från armbandet användes utöver muskelsignalerna syntes i bästa fall ingen förbättring av träffsäkerheten och i värsta fall en markant försämring.

MatLab code

The MatLab code written during this project.

```
%% Create Myo Object
% Instantiates Myo object
if exist('m') == 1
    clear
end
m = Myo();

EMGtrain = zeros(5600,8);
ACCtrain = zeros(800,1);

%%

clc;
FileID7 = fopen('PythonVars.txt','wt');
SampleRate = input('Sample rate (0-200Hz): ');
T = input('Duration (s): ');
pythonvars = [SampleRate, T];
fprintf(FileID7, '%d\n', pythonvars);
fclose(FileID7);
eval('!matlab -nodesktop -nosplash -minimize -r "r6 = 1, try,
terminate, catch, try, init_python, catch, exit, end, end" &')
t_initial = clock;
ii = 0;
t = 0;
a3 = [0 0 0 0];
a3_e = [0 0 0];

roll = 0;
pitch = 0;
yaw = 0;

a3_e(end+1,:) = [roll pitch yaw];
a5 = [0 0 0 0 0 0 0 0];

% FileID3 = fopen('Orientation.txt','w');
FileID5 = fopen('Emg.txt','w');

segment = ones(5,1);
export = zeros(30,8);
overlap = 5;

overlapcount = 0;
count = 0;
count2 = 1;
bilder = {'1.jpg', '2.jpg', '3.jpg', '4.jpg', '5.jpg', '6.jpg',
'7.jpg', '8.jpg'};
gest = 9;
```

```

global state;
state = [1 0];

global EMGsum;

performance = [1000,2];
gestgammal = 0;

while t < T
    ii = ii+1;
    t2 = clock;
    t(ii) = etime(t2,t_initial);
    % FileID3 = fopen('Orientation.txt');
    FileID5 = fopen('Emg.txt');
    % Orientation = textscan(FileID3,'%s %s %s %s');
    Emg = textscan(FileID5,'%s %s %s %s %s %s %s %s');
    % fclose(FileID3);
    fclose(FileID5);
    [p1,q1] = size(a5);
    [p2] = length(Emg{1});
    if (p1 < p2);

    % FileID3 = fopen('Orientation.txt');
    FileID5 = fopen('Emg.txt');
    [p5,q5] = size(a3);
    [p7,q7] = size(a5);
    % Orientation = textscan(FileID3,'%s %s %s
    %s','HeaderLines',p5);
    Emg = textscan(FileID5,'%s %s %s %s %s %s %s
    %s','HeaderLines',p7);

    % fclose(FileID3);
    fclose(FileID5);

    % for i = 1:length(Orientation{1});
    % s = {Orientation{1,1}{i,1} Orientation{1,2}{i,1}
Orientation{1,3}{i,1}, Orientation{1,4}{i,1}};
    % temp = strtok(s,'[ ]');
    % a3(end+1,:) = str2double(temp);
    %
    % [roll, pitch, yaw] = quat2angle(a3(end,:));
    % a3_e(end+1,:) = [roll pitch yaw];
    %
    % end

    for i = 1:length(Emg{1});
        s = {Emg{1,1}{i,1} Emg{1,2}{i,1} Emg{1,3}{i,1}
Emg{1,4}{i,1} Emg{1,5}{i,1} Emg{1,6}{i,1} Emg{1,7}{i,1}
Emg{1,8}{i,1}};
        temp = strtok(s,'[ ]');
        a5(end+1,:) = str2double(temp);

```

```

end

clc
count = count +1

% Sortera om exportvektorn som skall till classifier, räknar upp
hur många
% datapunkters overlap det är

    for i = 1:length(export(:,1))-1;
        export(i,:) = export(i+1,:);
        export(end,:) = [a5(end,:)];
    end
    overlapcount = overlapcount + 1;

% Exportera till classifier vilket returnerar en rörelse

if overlapcount == overlap
    overlapcount = 0;
    count2 = count2 +1;
    for i = 1:length(segment(:,1))-1;
        segment(i) = segment(i+1);
    end
    segment(end) = Classifier(export(:,1:8), mode(segment));
%     disp(segment);
end

% Classifiern har nu uppdaterat segment vektorn, mode funktionen är
en
% majority vote och säger vilken gest som skall outputas. Gesten
kan nu
% användas av state machine

        gest = mode(segment)
%         State_machine(gest);
%         disp(state);

% ### avkometera detta stycka för att visa bild på class label i
realtid

if gest ~= gestgammal
    gestgammal = gest
    imshow(bilder{gest}, 'Border', 'tight');
end

% Välj mellan att spara ren class label eller state i performance
vektorn,
% att plottas mot EMGsum.

%         performance(count,:) = [state(1) EMGsum];
%         performance(count,:) = [gest EMGsum];

```

```

%         subplot(1,2,1);
%         imshow(bilder{state(1)}, 'Border', 'tight');
%         subplot(1,2,2);
%         bar(state(2), 'r');
%         ylim([0 100]);
%         drawnow;

%         #####TRÄNING#####
% Sparar en matris av mätdata som används till träning ~230sec

%         [~,do] = max(EMGtarget2(count2,:))
%         if mod(count2-1, 200) == 0
%             imshow(bilder{do}, 'Border', 'tight');
%             pause(1);
%         end
%
%         EMGtrain2(count2,:) = Trainer(export(:,1:8));

%         #####VALIDERING#####
% Sparar en matris av mätdata som används till validering ~100sec

%         do = ACCTarget(count)
%
%         if mod(count-1, 100) == 0
%             imshow(bilder{do}, 'Border', 'tight');
%             drawnow;
%             pause(4);
%         end
%
%         ACCTrain(count,:) = gest;
%
% -----

        end
    end

    pyquit
    disp('Done');

    %%
    % räkna ut accuracy
    AccTester(ACCTrain, ACCTarget)

    %%

    % plotta EMG/class grafen

    hold on

    yyaxis left
    plot(performance(:,2));

```

```

refline(0,20);
ylabel('EMG activity');
yyaxis right
plot(performance(:,1), '*');
ylabel('Class label');

function [output] = Classifier(segment, current)
%CLASSIFIER - Får ett segemtn från myo programmet och
klassifiserear det

% Segment vektorn delas upp i åtta signaler, en från varje
elektrod
% olika varianter:
% Mean Absolute value - meanabs();
% Root Mean Square - rms();
% Variance - var();

c1 = meanabs(segment(:,1));
c2 = meanabs(segment(:,2));
c3 = meanabs(segment(:,3));
c4 = meanabs(segment(:,4));
c5 = meanabs(segment(:,5));
c6 = meanabs(segment(:,6));
c7 = meanabs(segment(:,7));
c8 = meanabs(segment(:,8));

% seg = [c1 c2 c3 c4 c5 c6 c7 c8 mean(roll) mean(pitch)];
% seg = [c1 c2 c3 c4 c5 c6 c7 c8 mean(roll)];
seg = [c1 c2 c3 c4 c5 c6 c7 c8];

global EMGsum
EMGsum = sum(seg);

[value,gest] = max(NNviktor3(seg));

output = current;
if value > 0.95
    output = gest;
end
function [seg] = Trainer(segment)
%Trainer - Får ett segemtn från myo programmet och gör det redo att
%användas till att träna nätverk

% Segment vektorn delas upp i åtta signaler, en från varje
elektrod
% olika varianter:
% Mean Absolute value - meanabs();
% Root Mean Square - rms();
% Variance - var();

c1 = meanabs(segment(:,1));
c2 = meanabs(segment(:,2));
c3 = meanabs(segment(:,3));
c4 = meanabs(segment(:,4));
c5 = meanabs(segment(:,5));

```

```

c6 = meanabs(segment(:,6));
c7 = meanabs(segment(:,7));
c8 = meanabs(segment(:,8));

% seg = [c1 c2 c3 c4 c5 c6 c7 c8 mean(roll) mean(pitch)];
% seg = [c1 c2 c3 c4 c5 c6 c7 c8 mean(roll)];
seg = [c1 c2 c3 c4 c5 c6 c7 c8];

function [] = State_machine(gest)
%STATE_MACHINE Summary of this function goes here
% Detailed explanation goes here

% maxvärdet på varje gests EMGsum, för normalisering
a = [1 300 200 300 200 200 300 200];

global state
global EMGsum

ramp = EMGsum/a(state(1));
ramp = ramp*5;
if ramp > 2;
    disp('hårt grepp');
else
    disp('svagt grepp');
end

if gest == 1
    return;
end

if state(2) == 0 && gest ~= 3
    state(1) = gest;
    state(2) = 1;
    return
end

if gest == state(1) && state(2) < 100
    state(2) = state(2)+5;
    if(state(2) > 100)
        state(2) = 100;
    end
    return
end

if gest == 3 && state(2) >0
    state(2) = state(2)-5;
    if(state(2) <= 0)
        state(2) = 0;
        state(1) = 1;
    end
    return
end
end
end

```