Using myoelectric signals for gesture detection: a feasibility study

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Abstract

The propose of this study was to assess the feasibility of using myoelectric signals acquired using an off the shelf device, the Myo armband from Thalmic Lab.

Background:
With the technological advances in sensing human motion, and its potential to drive and control mechanical interfaces remotely, a multitude of input mechanisms are used to link actions between the human and the robot. In this study we explored the feasibility of using human arm's myoelectric signals with the aim of identifying a number of gestures automatically.

Material and methods:
Participants ($n = 26$) took part in a study with the aim to assess the gesture detection accuracy using myoelectric signals. The Myo armband was used worn on the forearm. The session was divided into three phases, familiarisation: where participant learned how to use the armband, training: when participants reproduced a number of requested gestures to train our machine learning algorithm and recognition: when gestures presented on screen where reproduced by participants, and simultaneously recognised using the machine learning routines.

Results:
One participant did not complete the study due to technical errors during the session. The remaining ($n = 25$) participants completed the study allowing to calculate individual accuracy for grasp detection using this medium. Our overall accuracy was 65.06%, with the cylindrical grasp achieving the

highest accuracy of around 7.20% and the tripod grasp achieving lowest recognition accuracy of 60.15%.

Discussions:
The recognition accuracy for the grasp performed is significantly lower compared to our earlier work where a mechatronic device was used. This could be due to the choice of grasps for this study, as it is not ideal to the placement of the armband. While tripod, cylindrical and lateral grasps have different finger and wrist articulations, their demand on supporting forearm muscles (mainly biceps and triceps) is less definite and therefore their myoelectric signals are less distinct. Furthermore, drop in accuracy could be caused by the fact that human muscles and consequently the myoelectric signals are substantially variable over time. Muscles change their relative intensity based on the speed of the produced gesture. In our earlier study, the gesture production speed was damped by the worn orthosis, leading to normalising the speed of gestures. This is while in our current study, hand motion is not restricted. Despite these, the recognition accuracy is still significant.

Future work:
There are remaining questions related to the feasibility of using myoelectric signals as an input to a remote controlled robot in a factory floor as it is anticipated that such a system would enhance control and efficiency in production processes. These questions therefore require further investigations regarding usability of the armband in its intended context, to ensure users are able to effectively control and manipulate the robot using the myoelectric system and enjoy a positive user experience. Future studies will focus on the choice of gestures, so that they are distinct and better identifiable, but also on other key human factors and system design features that will enhance performance, in compliance with relevant standards such as ISO 9241-210:2010 (standards for human-system interaction ergonomic design principles) . Furthermore, aspects of whether a machine learning algorithm should use individually learned events in order to recognise an individual's gestures, or if it is possible to use normative representation of a substantial set of learnt events, to achieve higher recognition accuracy remains an interesting area for our future work.

Keywords: gesture detection, classification, machine learning, human-robot interface

1 Practitioner summary

With the technological advances in sensing human motion, and its potential to drive and control mechanical interfaces remotely, a multitude of input mechanisms are used to link actions between the human and the robot. In this study we explored the feasibility of using human arm's myoelectric signals with the aim of identifying a number of gestures automatically. We deployed machine learning tools to train and later identify gestures, and achieved an accuracy of around 65%. This indicates potential feasibility while highlighting areas for improvement both in accuracy and utility of such approaches.

2 Introduction

The problem of detecting hand posture has been approached using various methods such as vision-based and glove-based approaches. Vision based approaches often involve detecting the fingertips and inferring joint-articulations using inverse kinematic models of the hand and wrist skeleton (Chaudhary et al., 2013). Glove based approaches reduce the computation time by having a more-direct measurement of the articulations. Our earlier work using an electromechanical glove, the SCRIPT device, showed promising results in detecting pinch, lateral and cylindrical grasps. The glove measured the movements of hand and wrist which was fed to developed machine learning algorithms based on Support Vector Machines (SVM), that achieved a detection accuracy of around 91% in identifying the type of gesture performed. The methods held for identifying gestures for people recovering from neurological conditions such as stroke. (Leon et al., 2014a,b)

Another possible approach is to utilise myoelectric signals recorded from hand and wrist muscles in detecting gestures. Tavakolan et al. (2011) used SVM for pattern recognition of surface electromyography signals of four forearm muscles in order to classify eight hand gestures. They concluded that it was feasible to identify gestures using the four locally placed electrodes. Similarly, Wang et al. (2013) used linear discriminant analysis to achieve an average accuracy of around 98% in detecting 8 hand gestures using two electrodes placed on the forearm. Our study focuses on assessing the feasibility of using a commercially off the self device, the Myo armband from Thalmic labs, in detecting a number of hand gestures.

Outline The remainder of this article is organised as follows. Section 3 gives account of previous work, followed by the material and methods used in the current study. Our results are described in Section 4. Finally, Section 5 gives the conclusions.

3 Material and Methods

Machine learning techniques are used in a variety of biomechanical and biomedical assessments. (Oskoei and Hu, 2008; Begg et al., 2005; Foubert et al., 2012). In our earlier work, we utilised the Support Vector Machines (SVM) in order to automatically and quickly identify a grasp intention. Participants in the study worn a robotic glove which was used to record the motion of their hand and wrist, and their sensed motion was used in training and recognition of intended gestures. (Leon et al., 2014b). Our study showed acceptable accuracy of around 91% in detecting four grasps, tripod, lateral, cylindrical and rest positions as shown by figure 1.

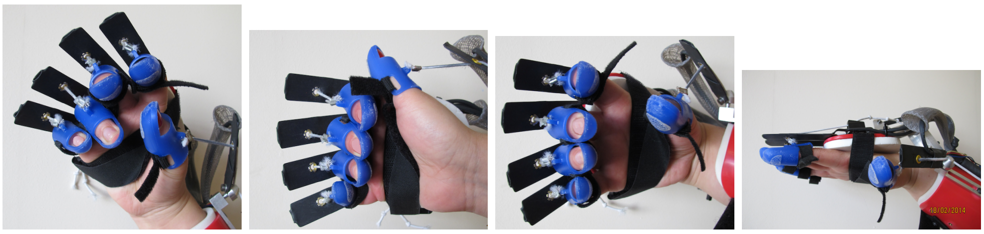

Figure 1: left to right: tripod, lateral, cylindrical and rest grasps presented with SCRIPT glove

In current study, we aimed at applying machine learning to identify gestures using a commercially off the shelf device, the Myo armband from Thalmic Lab[1]. The Myo armband is depicted in Fig 2. It benefits from 8 proprietary Electromyography (EMG) electrodes placed equi-distally around the arm utilising an ARM Cortex M4 processor to communicate via Bluetooth 4. The device offers haptic feedback as well as position tracking using accelerometers, gyroscope and magnetometers. Unlike earlier studies where individual electrodes are applied to flexor and extensor muscles, the Myo armband offers the possibility of positioning the electrodes at a relatively fixed location with respect to one another. This was thought to have an impact on reducing the variability caused by electrode placement. An application was developed using ROS, Robot Operating System[2], that allowed for reading from individual electrodes and conducting this experiment. ROS was used to allow for future testing of the interface with robots.

[1] https://www.thalmic.com/en/myo/
[2] www.ros.org

Figure 2: Myo armband from Thalmic Labs

3.1 Experiment Design

An experiment was designed consisting of three phases. During phase A, participants made themselves familiar with the arm band and its operation. During this time, participants tried 4 gestures that are currently detected by the device software. These gestures were closed fist, hand open with fingers spread, wrist fully flexed and wrist fully extended as depicted in Fig 3. When participants are confident in using the device, they then moved to the next phase.

Figure 3: Gestures used for familiarisation with Myo. Left to right: Closed fist, fingers spread, wrist flexed and wrist extended

In phase B, known as the training phase, participants tried one of the four gestures in Table 1 were presented in random order on screen. Each image was presented for 5 seconds, and electrode readings logged at 60Hz. Once all of the four gestures were performed 5 times, participants moved to the next phase of the study.

In phase C, or the recognition phase, the same gestures used in Phase B are shown on screen. This time produced gesture is recognised using a machine learning algorithm (detailed under 3.3) and the resulting gesture code is labelled as $\{0, 1, 2, 3\}$ and logged alongside the presented gesture codes at 60Hz. Overall,

Table 1: Gestures used in training (A) and recognition (B) phases

Grasp code	Grasp Type
0	Closed fist
1	Tripod grasp
2	Lateral grasp
3	Cylindrical grasp

considering the three phases, a typical experiment session is shorter than 15 minutes.

3.2 Participants and Experiment setup

The experiment protocol was approved by the University of Hertfordshire's ethics committee under the approval number COM/PGR/UH/02057. A total of 26 participants accepted to take part in the study. All participants offered written consent prior to participation. Participants sat in front of a 21 inch monitor, wearing the Myo armband on their dominant arm. The forearm was rested on a Saebo MAS arm support to limit additional muscle contractions. The experimental setup is offered in Fig 4.

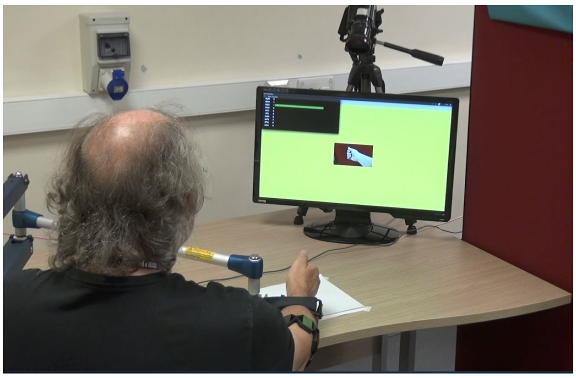

Figure 4: Experimental setup

During the experiment, due to technical issues, one participant did not complete the study. All remaining participants ($n = 25$) completed the three phases of the study.

3.3 Methodology

Our earlier study with SCRIPT device showed promising results for using machine learning in identifying gestures with an electromechanical glove. In the current study we thought to assess the utility of another approach in machine learning, the k-nearest neighbour's method. This is an instance-based classification mechanism where values of a new observation are compared to the training samples with the goal of finding a predefined number of training samples, k, with the closest distance to the observation. The distance parameter is often the Euclidean distance between the observation and the training data (Friedman et al., 1977; Dasarthy, 1991; Shakhnarovich et al., 2006).

We used the python machine learning kit[3] to apply this algorithm in order to label observations with their recognised labels from Table 1. The number of nearest neighbours was set to 15 ($k = 15$). To remember the training data, an indexing approach known as 'KD Tree' is used for fast indexing. When a queried gesture was close to a cluster of trained gestures, the trained gesture's label was used to label the query gesture. As the queried gesture was initialised by following onscreen instruction to produce a gesture, it was possible to link the recognised gesture to the one intended.

4 Results

Each participant repeated the four gestures in Table 1 for a minimum of 5 times during the recognition phase of the experiment. Each of the gestures were recorded for 5 seconds under each repetition. The logged data coded participant ID, required gesture, detected gesture and the distance calculated for the nearest 15 neighbours. By comparing the required gesture to the detected gesture, it was possible to calculate the recognition accuracy for each participant and each gesture.

Figure 5 shows the overall accuracy ($M = 65.06, SD = 5.01$) for each participant in the study.

Figure 6 shows the detection accuracy variations between different gestures.

Figure 7 shows the variation between different gesture detection accuracies performed by different participants.

Table 2 shows the average accuracy values for each gesture.

[3] http://scikit-learn.org/stable/index.html

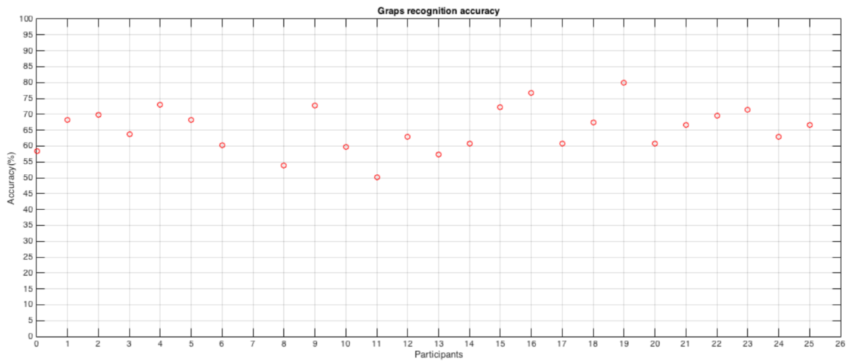

Figure 5: Overall recognition accuracy for study participants

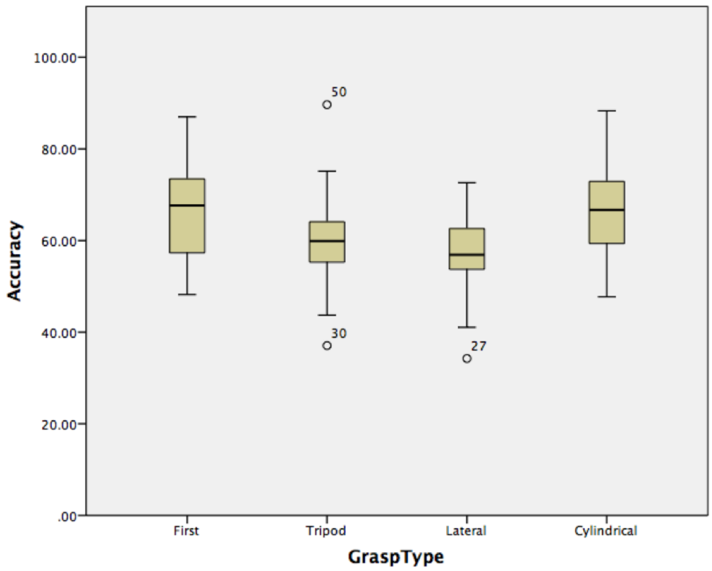

Figure 6: Recognition accuracy variation between different gestures

5 Discussions and Conclusions

STILL WORK IN PROGRESS The overall recognition accuracy and the accuracy of recognising each grasp type is significantly lower than our earlier study where a mechatronic device is used to capture human arm and wrist articulations. The variations in accuracy could be due to a number of factors.

A) The differences between gestures captured by angular recording of fingers and wrist articulations are incomparable to that captured by recording the myo-

Table 2: Mean and standard deviation of recognition accuracy for different grasp types

Grasp code	Grasp Type	Mean Recognition Accuracy	SD
0	Fist	66.45	10.89
1	Tripod	60.64	10.91
2	Lateral	57.31	9.75
3	Cylindrical	66.57	11.09

electric signals from the forearm. The 4 chosen gestures trained and recognised present very similar muscle involvements specially when captured using the electrode arrangements around the arm. The success of the Tavakolan et al. (2011) and Wang et al. (2013) could be indeed due to the freedom in electrode placement. In our study, we did not discriminate between electrodes placed on flexor and extensor muscles and such information cab be used to improve the machine learning. This could also be due to the choice of machine learning approach. We intend to explore this by applying multiple machine learning approaches to the data to assess if recognition accuracy changes.

B) Differences between the results from SCRIPT device and the current study

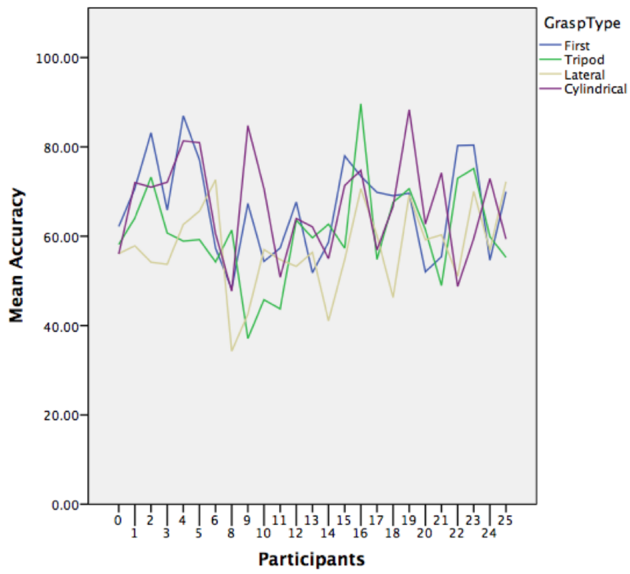

Figure 7: Recognition accuracy variation between different gestures

could also be due to damping effects of a worn exoskeleton compared to free hand movements captured here. Due to the freedom of the hand to move at its natural speed, there are larger variations in EMG recordings that are caused by change in relative intensity of involved muscles.

5.1 Role of human factors

The current study involved a limited consideration of human factors because the early focus of this research programme is to first develop the technical feasibility of the myoelectric system. Having achieved this, a number of human factors design issues can now be explored. For example, it will be important to explore aspects of the system that impact on usability, user experience and acceptance and well-being as well as performance. These investigations will focus on making sure applications in specific contexts conform to current standards for technical and ethical design and application.

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