Using myoelectric signals for gesture detection: a feasibility study

Farshid AMIRABDOLLAHIAN*, Michael WALTERS*, Rory HEFFERNAN*, Sarah FLETCHER**, Phil WEBB**

**University of Hertfordshire, United Kingdom, ** Cranfield University, United Kingdom*

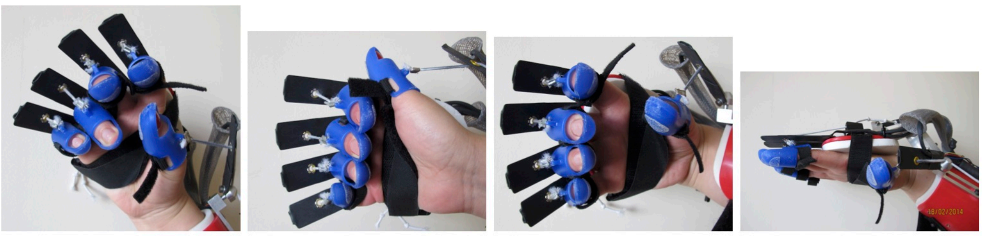
Abstract. With the technological advances in sensing human motion, and its potential to drive and control mechanical interfaces remotely, a multitude of input mechanisms are used to link actions between the human and the robot. In this study we explored the feasibility of using the human arm's myoelectric signals with the aim of identifying a number of gestures automatically. We deployed k-nearest neighbour's algorithm in machine learning 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/usability of such approaches.

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

1. Introduction

The problem of detecting hand gesture 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. These were fed into developed machine learning algorithms based on Support Vector Machines (SVM), that achieved a gesture-type detection accuracy of around 91%. The methods held for identifying gestures for people recovering from neurological conditions such as stroke. (Leon et al., 2014a,b)

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



glove

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 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.

2. Material and methods

In the current study, we aimed at applying machine learning to identify hand and wrist gestures using a commercial 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 equidistally 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 at different places along the arm length, 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.

Figure 2. Myo armband from Thalmic Lab

2.1. Experiment Design

A 3-phase experiment was designed. During phase A, participants made themselves familiar with the arm band and its operation and tried 4 gestures that are currently detected by the device software: closed fist, hand open with fingers spread, wrist fully flexed and wrist fully extended (as depicted in Figure 3). When participants were confident in using the device, they moved on to the next phase.

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

In phase B, the training phase, participants tried one of four gestures (0: Fist ; 1: Tripod Grasp; 2: Lateral Grasp; 3: Cylindrical Grasp) presented in random order onscreen for 5 seconds, and electrode readings logged at 60Hz. Once all four gestures were performed 5

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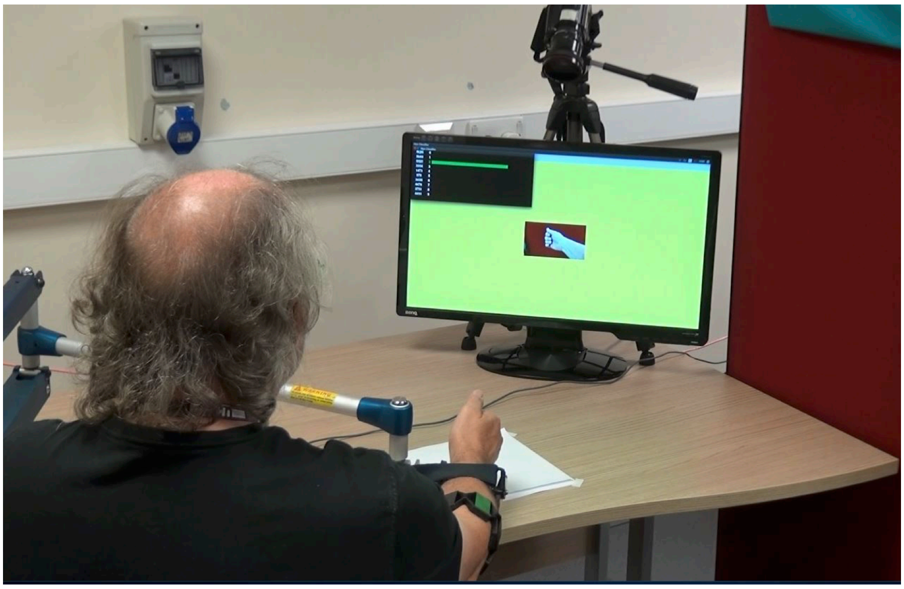
[1] https://www.thalmic.com/en/myo/

[2] www.ros.org

times, participants moved to the next phase.

In phase C, the recognition phase, the same gestures used in Phase B were shown onscreen. This time the produced gesture was recognised using a machine learning algorithm (detailed under 3.3) and the resulting gesture code was labelled as (0,1,2,3) and logged alongside the presented gesture codes at 60Hz. A typical experimental session for the 3 phases was less



than 15 minutes.

2.2. Participants and experiment setup

The experimental protocol was approved by the University of Hertfordshire's ethics committee (approval number COM/PGR/UH/02057). A total of 26 participants agreed to take part. All were offered written consent beforehand. Participants sat in front of a 21" 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 shown in Figure 4. One participant did not complete the study due to technical issues. The rest (n = 25) completed all three phases.

2.3 Machine learning method

The utility of another approach in machine learning, the k-nearest neighbour's method was also assessed. 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 to label observations with their trained labels. The number of nearest neighbours was set to 15 (k = 15). To remember

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

the training data, an indexing approach known as 'KD Tree' was 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 queried 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.

Figure 4. Experiment setup

3. Results

Each participant repeated each gesture 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 the 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.

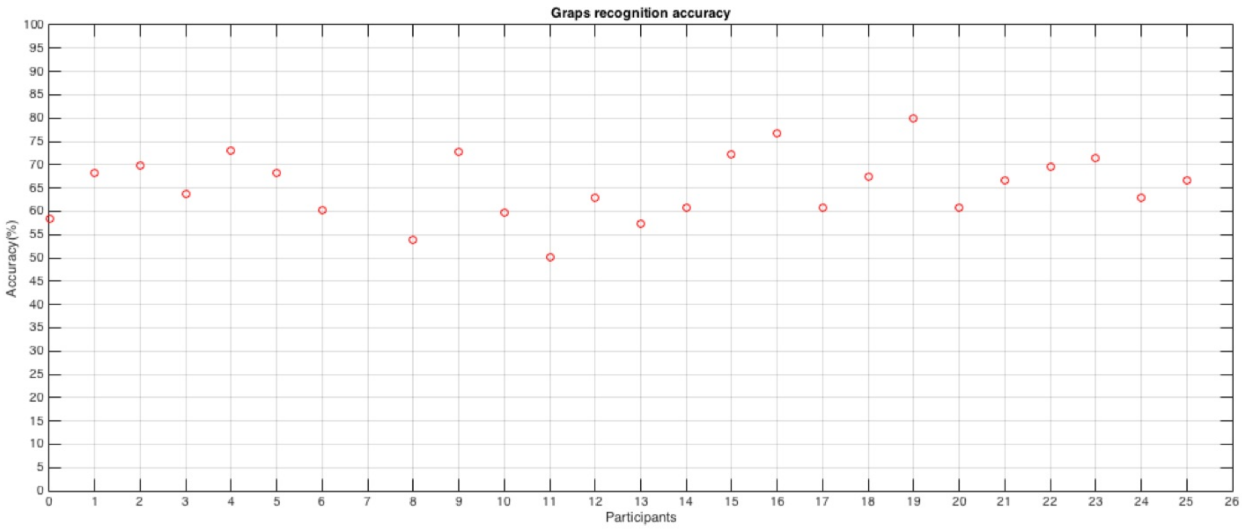


Figure 5. Overall recognition accuracy for study participants

Figure 6 shows the detection accuracy variations between different gestures (Fist: M = 66.45, SD = 10.89; Tripod: M = 60.64, SD = 10.91; Lateral: M = 57.31, SD = 9.75; Cylindrical: M = 66.57, SD = 11.09)

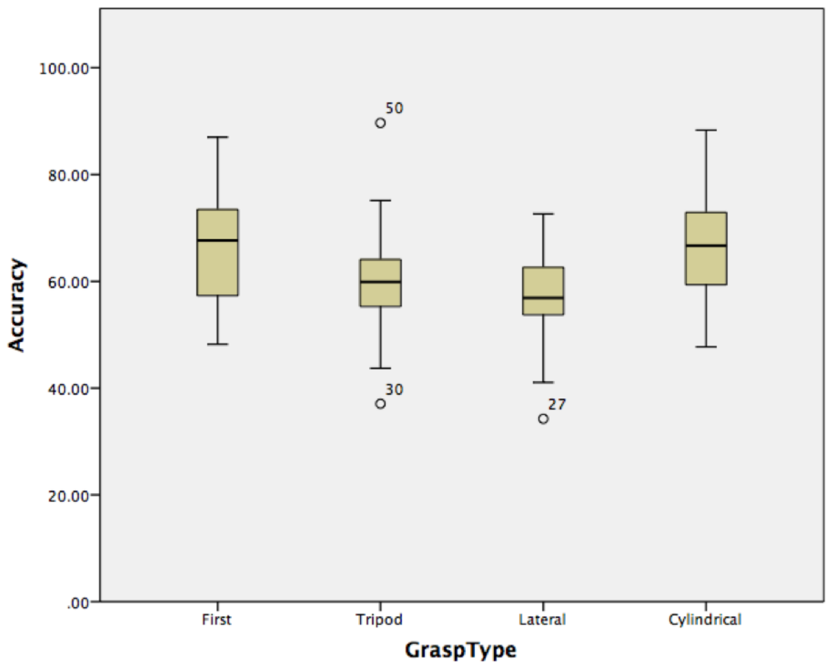


Figure 6. Recognition accuracy variation between different gestures (for all subjects)

4. Discussion and Conclusion

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 for the placement of the armband. While tripod, cylindrical and lateral grasps have different finger and wrist articulations, their demand on supporting forearm muscles (flexor and extensor pairs) is less definite and therefore their myoelectric signals could be less distinct, especially when captured by electrodes placed around the arm as done in Myo. Studies of Wang et al. and Tavakolan et al. achieved better accuracy when electrodes were placed at different locations along the length of the arm. Another difference between these studies and the current one was the choice of a machine learning approach. We intend to repeat this analysis using the SVM approach (as used in the earlier study) to measure accuracy gains.

The drop in accuracy could also have been 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 why hand motion is not restricted in the current study. Despite this, the recognition accuracy is still significant.

5. Future work

Questions remain on the feasibility of using myoelectric signals as an input to a remote-controlled robot on a factory floor as it is anticipated that such a system would enhance control and efficiency in production processes. So this requires further investigation into the 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; 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); 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.

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