Application of support vector machines to detect hand and wrist gestures using a myoelectric armband

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Abstract

The propose of this study was to assess the feasibility of using support vector machines in analysing 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 or to be used as input interfaces, 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 participants learned how to use the armband, training: when participants reproduced a number of random gestures presented on screen to train our machine learning algorithm; and recognition: when gestures presented on screen were reproduced by participants, and simultaneously recognised using the machine learning routines.
Support vector machines were used to train a model using participant training values, and to recognise gestures produced by the same participants. Different Kernel functions and electrode combinations were studied. Also we contrasted different lengths of training values versus different lengths for the recognition samples.

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. The overall accuracy was 94.9% with data from 8 electrodes , and 72% where only four of the electrodes were used. The linear kernel outperformed the polynomial, and radial basis function. Exploring the number of training samples versus the achieved recognition accuracy, results identified acceptable accuracies ($> 90\%$) for training around 3.5s, and recognising grasp episodes of around 0.2s long.
The best recognised grasp was the hand closed (97.6%), followed by cylindrical grasp (96.8%), the lateral grasp (94%) and tripod (92%).

Discussions:
The recognition accuracy for the grasp performed is similar to our earlier work where a mechatronic device was used to perform, record and recognise these grasps. This is an interesting observation, as our previous effort in aligning the kinematic and biological signals had not found statistically significant links between the two. However, when the outcome of both is used as a label for identification, in this case gesture, it appears that machine learning is able to identify both kinematic and electrophysiological events with similar accuracy.

Future work:
The current study considers use of support vector machines for identifying human grasps based on myoelectric signals acquired from an off the shelf device. Due to the length of sessions in the experiment, we were only able to gather 5 seconds of training data and at a 50Hz sampling frequency. This provided us with limited amount of training data so we were not able to test shorter training times ($< 2.5s$). The device is capable of faster sampling, up to 200Hz and our future studies will benefit from this sampling rate and longer training sessions to explore if we can identify gestures using smaller amount of training data.

These results allows us to progress to the next stage

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of work where the Myo armband is used in the context of robot-mediated stroke rehabilitation.

1. 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 the wrist skeleton [1]. 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. [2, 3]

Another possible approach is to utilise myoelectric signals recorded from hand and wrist muscles in detecting gestures. Tavakolan et al. 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 [4]. Similarly, Wang et al. used linear discriminant analysis to achieve an average accuracy of around 98% in detecting 8 hand gestures using two electrodes placed on the forearm [5]. 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 using machine learning algorithm, particularly the support vector machines.

2. MATERIAL AND METHODS

A variety of biomedical and biomechanical assessments benefit from machine learning techniques. In a pioneering work, Doerschuk et. al explored using EMG signals to control a lower limb prosthetic arm and wrist [6]. Huang and Cheng extended the work into identifying a number of hand gestures [7] . Oskoei et. al assessed the use of support vector machines in order to identify the optimal feature set and kernels. Their study provided a comprehensive review of the techniques used and different available feature sets. [8]

In our earlier work, we utilised 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. [3]. Our study showed acceptable accuracy of around 91% in detecting four grasps, tripod, lateral, cylindrical and rest positions as shown by figure 1.

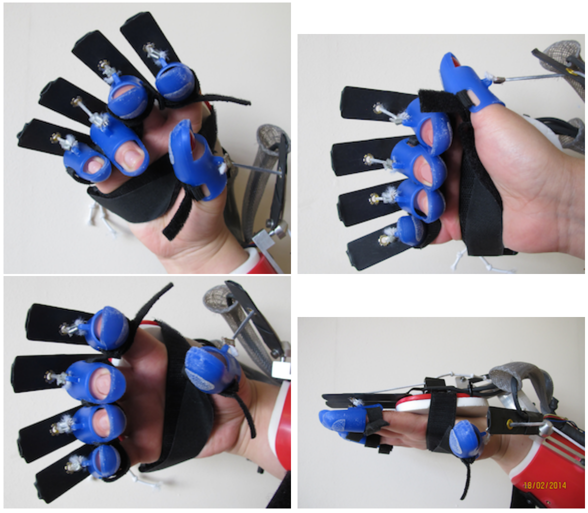

Figure 1. left to right: tripod, lateral, cylindrical and rest grasps presented with SCRIPT glove

In the 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 consists of 8 proprietary Electromyography (EMG) electrodes placed equidistally around the arm utilising an ARM Cortex M4 processor to communicate via Bluetooth 4. The device offers position tracking using accelerometers, gyroscope and magnetometers, and also haptic feedback in form of vibration. 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. Electrode application is simple and the device can be worn at home without assistance. We used the Robot Operating System[2] to develop an application that acquired data from individual electrodes. ROS was used to allow for future testing of the interface with robots.

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

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Figure 2. Myo armband from Thalmic Labs

2.1. Experiment Design

The designed experiment had 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. As these gestures were performed by each participant, the relevant image showing the hand in its recognised gesture appeared on screen. Familiarisation gestures were closed fist, hand open with fingers spread, wrist fully flexed and wrist fully extended as depicted in Fig 3. When participants were 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, the training phase, participants tried one of the four gestures in Table 1 that were presented in a random order on screen. Each image was presented for 5 seconds, and electrode readings logged at 50Hz. Once all of the four gestures were performed 5 times, participants moved to the next phase of the study.

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

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 the a machine learning algorithm (detailed under 2.3) and the resulting gesture code is labelled as $\{0, 1, 2, 3\}$ and logged alongside the presented gesture codes at 50Hz. Overall, considering the three phases, a typical experiment session is shorter than 15 minutes.

2.2. 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 consented to take part in the study. 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 5.

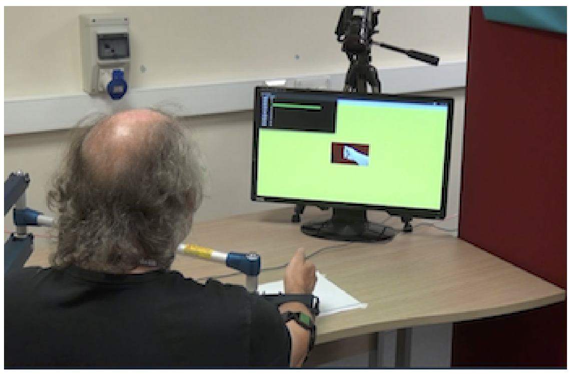

Figure 4. Experimental setup

During the experiment, due to technical issues, one

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participant did not complete the study. All remaining participants ($n = 25$) completed the three phases of the study.

2.3. Methodology

Our earlier study with SCRIPT device showed promising results for using machine learning in identifying gestures with an electromechanical glove. In the followup work, we continued to assess the utility of multiple approaches in machine learning in detecting gestures using myoelectric signals. The study of k-nearest neighbour method in classifying myoelectric signals resulted in [9]. This paper focuses on utility of SVM in gesture classification. To do so, it utilises the data recorded during the second phase of the study where participants repeated performed random gestures for a duration of 5 seconds, 5 times.

2.3.1. Recognition using support vector machines. Support vector machines are increasingly popular tools for machine learning. The support vectors are constructed optimal hyperplanes in a multidimensional feature space. They allow for clustering and separation of the data classes, but also allow to assign class labels to new observations. The theoretical background and how these machines work in further details is offered in [10] and its application in analysing human-robot sensed interaction is presented by Leon et. al [2], and the application in assessing electromygraphy data is detailed by Oskoei and Hu [8]. Both application examples utilise the *libsvm*, a powerful library for support vector machines [11] which has been also used for the analysis presented in this paper.

For the data preparation in this paper, the recorded data obtained from phase 2 of the experiment, the familiarisation is divided into two parts, one part is used for training while the second part is used to test the trained machine. We have experimented with different training/recognition segment lengths in order to identify the best recognition accuracies. Raw data recorded from the EMG sensors in the Myo armband are recorded as an array of 8 values with a 50Hz sampling rate. Before any training is done, we had to identify a potent feature set or objective representation. Oskoei and Hu showed that the waveform length (WL) feature is capable of detecting gestures with an acceptable and robust performance [8]. Huang and Chen [7] offer the waveform length as:

$$WL = \sum_{k=1}^{n} |x_k - x_{k-1}| \qquad (1)$$

Noting that the minimum interval between two distinct muscle contraction is approximately 200ms [12] and that this segment length had been found to be the suitable length for a SVM application [8], we used $k = 10$ to reduce the data to 200ms interval features which are then used for machine learning and classification.

We derived the training and recognition sets for each participant by considering different lengths for the training $training\_s \in \{2.5, 3.0, 3.5, 4.0\}$ seconds and also for different lengths for the recognition seconds as $recognition\_s \in \{0.2, 0.4, 0.6, 0.8, 1.0\}$. We used python *libsvm* libraries and passed the training data through an initial assessment (*easy.py* from the *libsvm* tools) to identify the kernel parameters. Each problem set consisting of a training and classification set are treated to identify a pair of (c, γ) training parameters. With these known, a problem is passed to three different kernels, the linear, polynomial and RBF kernels. The resulting recognition accuracies are then gathered in a *CSV* file and analysed using IBM SPSS version 23.

3. RESULTS

We experimented with 3 different kernels as offered in table 2. The table shows the differences in overall recognition accuracy for the same amount of training data used for each kernel:

Table 2. Training accuracy for different SVM kernels

Kernel	Accuracy (mean)	Std. Deviation
Linear	94.90	11.13
Polynomial	89.80	14.71
Radial Basis Function	31.10	20.48

This identified the linear kernel as the most accurate kernel to be used for the training and recognition. A similar trend was visible when comparing the kernel performance between different grasps.

The next comparison explores accuracy gains based on different training and recognition sample lengths as offered by choices in $training\_s$ and $recognition\_s$.

This identified the $training\_s = 2.5$ and $recognition\_s = 0.2$ as the most accurate (94.9 ± 11.13) lengths for this classification problem. Table 3 shows the detection accuracy for different gestures with the optimal training and recognition lengths:

Fig 6 presents the accuracy of grasp recognition for different participants in this study, performing different gestures.

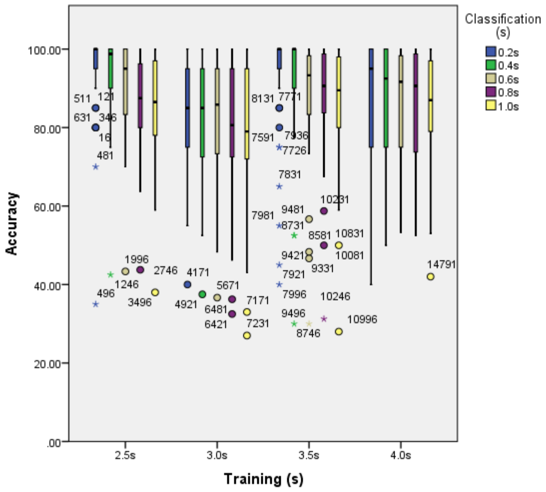

Figure 5. Recognition accuracies for different training and recognition lengths

Table 3. Training accuracy for different grasps in this study

Gesture	Mean	Std. Deviation
Fist	97.60	9.59
Cylindrical	96.80	11.68
Lateral	93.20	19.63
Tripod	92.00	22.13

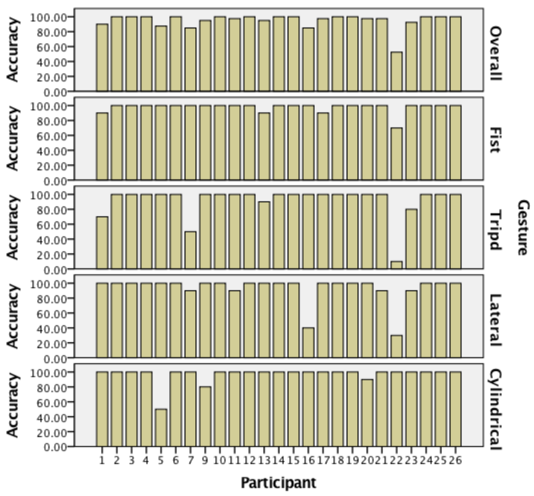

Figure 6. Recognition accuracies for different gestures performed by participants

Finally, the Myo armband utilises 8 electrodes placed around the arm. We explored whether a similar recognition can be achieved if only 4 of these electrodes were used. This resulted in a overall recognition accuracy of 72%.

4. DISCUSSIONS & CONCLUSIONS

This study compared the recognition accuracy of detecting gestures using myoelectric signals acquired from the commercially off the shelf device, Myo armband. We compared recognitions between different kernels and concluded that the linear kernel out performed the polynomial and RBF kernels. This is different to the results offered by Oskoei and Hu [8] showing similar performances across these kernels. Our study used a significantly lower sampling frequency (50Hz compared to a 1000Hz in the cited study). Also our study acquired the signals from muscles located at a cross-section of the arm covered by the armband while Oskoei and Hu acquired the signals from electrodes placed at different locations along the length of the arm. In our next study we will take full advantage of the whole 200Hz sampling rate available to compare if different kernel performances would be improved given this.

We applied the waveform length to compare recognition accuracy for different amounts of training and recognition data. Our results indicated that a 2.5s training data repeated 5 times is capable of returning acceptable accuracies for 0.2s of the recognition data from the same gesture/grasp. Expectedly, longer recognition data has larger deviation and drop in accuracy. An interesting observation here is that recognition results for 2.5s and 3.5s of the training data are similar, while recognition results for 3.0s and 4.0s of training data are also similar to one another (see Fig 5). We hypothesise that this results from a chance assignment of training length iterations (increase by 0.5 seconds per problem) that may better contain waveform length related to the full grasps. Participants in this study produced the training grasps using the required grasp's image on screen and it could be argued that different grasp speeds as well as perception times needed to produce the grasps may result in different accuracies observed. To ascertain this, we currently plan a study that provides the required grasp in an animated form on screen accompanied by audio prompts, thus to ensure all participants produce the exact gestures in a given time, and also to explore further the link between grasp accuracy similarities observed here. This will also allow us to shed further light into cases where grasp recognition accuracy is significantly lower, for example in the case of participant 22 where all gestures but the cylindrical grasp show lower recognition accuracy. In this case, the optimisation process estimating the pair of (c, γ) parameters did not manage to reach an optimal solution given the extent of training data offered. Further exploration in this area will allow us to identify if Myo arm band offers a reliable source of data for all participants, and whether additional training data can offer better recognition accuracies in such cases.

This study presented reasonable accuracies for the grasps examined enabling us to move to the next phases where these grasps can be automatically detected using the trained support vectors, thus enabling us to provide a more accurate interactive rehabilitation exercise. Our future studies will aim at reducing the standard deviation shown in Table 3 thus to make the interaction more reliable. Also we acknowledge that this study has performed the analysis with healthy individuals in a laboratory setting, while intended target users are people recovering from stroke. Our findings will be re-examined in a similar experiment with the intended users in future studies.

Lastly, we aimed at identifying if a commercially available off-the-shelf device would provide sufficient data for the machine learning models. We confirm this with a our limited 50Hz sampling assignment, a small amount of training data that can be captured in a calibration phase or personalisation phase of a human-robot interaction session. Our next planned study will compare this performance to a medical TMSI amplifier with clinical EMG.

The current experiment gather data from a short-time use of the device and a remaining question relates to repeatability of these results after a longer exposure and use in different days and different times of the day. These remain a motivation for our future studies.

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