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RESEARCH ARTICLE

Intuitive Electromyographic Control of the SPAR Glove

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Abstract
The SPAR Glove, a semi-rigid hand exoskeleton, has been developed to assist activities of daily living (ADL) for individuals with upper extremity impairment arising from neuromuscular injury. The glove detects user intent via a MYO armband, a wearable electromyography (EMG) device. In this manuscript, a control scheme is demonstrated that uses pattern recognition tools to infer the desired hand pose from the EMG activity. The ability of the measurement and classification methods to distinguish between hand poses was evaluated with nine able-bodied participants and three participants with spinal cord injury (SCI) in an offline experiment. The strong performance of the proposed intent detection method is shown in both the classification accuracy, presented as confusion matrices, as well as the average confidence for each classification. Building upon the strong performance in detecting pose, a pilot study with two participants with SCI presents the initial results of the real-time implementation of the system, which suggests directions for future work in improving the classification accuracy through expanded measurement and a refined taxonomy.

1. Introduction

Each year approximately 17,000 people experience a spinal cord injury (SCI) that impairs motor function (National Spinal Cord Injury Statistical Center (2017)). Many of these individuals retain some ability to move their upper extremities but lack the strength to produce enough movement to complete tasks associated with activities of daily living (ADL). Assistive devices have the potential to help these individuals regain some level of functional independence, by increasing the strength of movement and by increasing the dexterity of individual digits on the hand. Surveys of SCI participants confirm that such an increase in dexterity would represent a significant increase in their quality of life (QOL), as 71% of people with tetraplegia require assistance with these activities (Collinger et al. (2013)). The ability to perform ADL independently greatly increases the range of activities in which individuals can participate and reduces the costs associated with their care. With improved hand function and independence, people who have suffered an SCI can seek employment, improving their finances as well as their participation in their communities, resulting in improved QOL (Dijkers (1997)).

Assistive devices may also contribute to improved *rehabilitation* outcomes for those with incomplete SCI, by providing support for functional tasks that might in turn result in increased use of the impaired limbs. Many individuals undergo physical therapy following SCI, and this has proven effective at increasing neuro-plasticity reward (Edgerton et al. (2004)). Evidence has shown that high-intensity and repetitive practice can lead to recovery of some spinal cord, and therefore extremity, function (Dietz et al. (2002)). Further, functional training has shown to have beneficial effects in promoting spinal plasticity which can help lead to recovery (Dietz and Fouad (2014); Behrman et al. (2006)).

Assistive devices, particularly those compatible with at-home use, may be uniquely suited to address the need for increased functional training. Incorporating functional tasks has been shown to be beneficial in the rehabilitation of stroke survivors, and it is reasonable to expect that the same would hold true for individuals with SCI (Kristensen et al. (2011); Legg et al. (2007)). This expectation is supported by animal model studies (Cai et al. (2006); van den Brand et al. (2012)). Further, functional training has shown to have beneficial effects in promoting spinal plasticity, which can help lead to recovery (Dietz and Fouad (2014); Behrman et al. (2006)). Performance of ADL, with the supportive of an assistive device, therefore not only provides a useful platform for physical therapy, it helps the participant enhance skills that directly improve their QOL. Frequent usage of therapeutic assistive devices therefore has the potential to create a feedback loop wherein continued practice improves ability, increased ability results in more frequent use, and more frequent use results in additional practice and therefore increased gains in ability level (Winstein et al. (1999)). Though there was evidence that motor impairment was improved through robotic therapy for the 120 devices surveyed by Maciejasz et al. (2014), the ability to perform ADL was not enhanced any more than conventional therapies. This opens up a window for development of a device that specifically addresses movement associated with ADL.

1.1. Assisting Hand Function

When considering the requirements of an assistive device intended to support functional hand movements or poses, one should consider the poses that most contribute to the execution of high-level tasks common to ADL. For example, Dollar (2014) catalogued a comprehensive set of grasps involved in ADL. In related work, Dalley et al. (2011) identified a set of seven poses, shown in Figure 1, that are necessary to accomplish most ADL, and used them as the basis for an intuitive control scheme for a commanding a multi-DOF prosthesis.

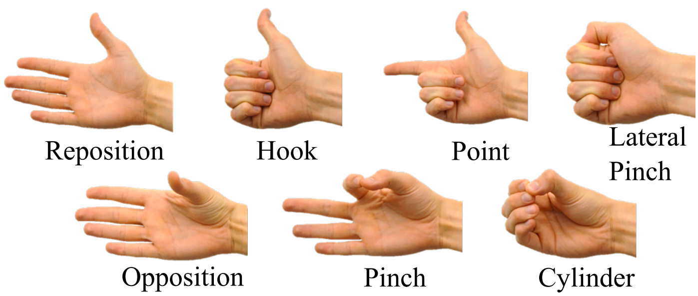

Figure 1. The taxonomy proposed by Dalley et al. (2011) consists of the pictured seven hand poses which were identified as critical to accomplishing the majority of ADL. This set of poses served as the basis for design of a myoelectric control scheme for a multi degree-of-freedom hand prosthesis.

A number of different assistive and rehabilitative devices intended to support hand function have been proposed in recent years, and these devices increasingly rely on soft components or soft actuators (see Chu and Patterson (2018) for a review). In general, soft devices tend to sacrifice power for compliance and flexibility. In contrast, rigid devices offer enhanced strength at the expense of added bulk and weight, frequently making them prohibitive for use outside the clinical setting. In an attempt to obtain benefits from both approaches, Rose and O'Malley (2019) introduced the SeptaPose Assistive and Rehabilitative (SPAR) Glove as a compromise design between the two extremes. The SPAR Glove is a semi-rigid exoskeletal device combining the flexibility of softgoods with the strength of rigid designs, consisting of a commercially available work glove with additional features sewn on. Other devices including the HERO Glove by Yurkewich et al. (2020) and the ExoGlove PM by Yun et al. (2017) also use this hybridized approach. Hybrid devices tend to have more degrees of freedom and larger torque output than their soft counterparts, making them well-suited to supporting functional hand poses needed to interact with everyday objects. Despite these hardware advances, more intuitive user interfaces are needed to enable intuitive control of these assistive gloves.

1.2. Detecting User Intent for Assistive Device Control

Intent detection, as defined by Losey et al. (2018), is the passing of information about the human planned action to the robot through a defined channel of communication. Led by the prosthetic community, most current, commercial devices opt for myoelectric control or body-powered control (Fougner et al. (2012)), with advanced brain machine interfaces (BMI) largely remaining in the lab and clinic (Shanechi (2017)). Within the field of wearable assistive devices (reviewed by Chu and Patterson (2018)), intent detection is split along similar lines, with coupling between less-impaired joints and electromyography (EMG) control correspond to body powered and EMG prostheses, respectively, with the added use of pressure sensors at the fingers as the most frequently used modalities for orthoses. Typically, these control schemes use dichotomous open/close architecture. Of the 44 unique devices they reviewed, only 13 presented a form of intent detection. Where used, that intent detection took the form of manual selection, kinematic couplings, finger commands, and EMG.

1.2.1. Manual Selection

Manual designs, relying on the user to operate switches or buttons, such as the system proposed for HES by Conti et al. (2017), trades unobtrusiveness for ease of operation and unequivocal intent detection. Voice commands have also been implemented with versions of the X-Glove (Triandafilou et al. (2011); Fischer et al. (2016)) called the VAEDA Glove (Thielbar et al. (2017)), to select the device state.

1.2.2. Kinematic Coupling

The Exo-Glove (In et al. (2015); Jeong et al. (2013)) used bend sensors at the wrist to control grasp aperture, following the tenodesis grasp which is often trained during therapy. The tenodesis grasp relies on an individual's residual motion in the wrist to take advantage of the biomechanical coupling of wrist flexion and extension to passively move the coupled joints of the finger (Johanson and Murray (2002)).

1.2.3. Finger Commands

Grouped into flex and pressure sensors at the digit by Chu and Patterson (2018), using the fingers themselves to control a hand exo is very suitable for devices with healthy or lightly impaired users. This approach has been implemented in the RoboGlove (Diftler et al. (2015)) and the SEM Glove (Nilsson et al. (2012)). Similar methods can be implemented with bend sensors at the finger, where the device will move in response to motion of the hand (Toya et al. (2011)). However, these modalities can prove difficult to control for impaired users with little voluntary control of their fingers, and can reduce dexterity and sensation because sensors have been implemented on surfaces crucial for stable grasps.

1.2.4. Electromyographic Control

EMG control of wearable, orthotic devices is rapidly becoming a standard, following developments in the prosthetics community (Fougner et al. (2012)), particularly with strategies for overcoming underactuation and taxonomy based designs (Santello et al. (1998)). Designs such as J-Glove (Ochoa et al. (2009,0)) intended for use with a post-stroke population, aims to assist in extension of all five fingers with a single motor, and use EMG to detect intent and promote engagement. The main therapy control mode is a triggered mode, where a certain EMG activation threshold must be overcome before the motor will move in 10% of total movement increments. The goal of this stepped response is to require users to remain engaged throughout the movement (Ochoa et al. (2011)). Many devices detect EMG activation across a predefined window, and return force based on the the proportion of the current signal to maximum voluntary effort, as implemented on cable driven (Delph et al. (2013)), and pneumatic devices (Zhao et al. (2016); Polygerinos et al. (2015)). The VAEDA Glove used EMG for triggered control modes (device is open-loop after a user initiates motion by crossing a threshold) but continuous modes can be implemented (Thielbar et al. (2017)). The work of Kadowaki et al. (2011) sought to discriminate between wrist and finger activity, but also limited command to flexion and extension of a single degree of freedom. Dwivedi et al. (2019) commanded multiple poses to a device, but the poses were predetermined by a menu of buttons with the EMG serving only as a trigger for the selected pose.

However, EMG is capable of providing more specific, granular information beyond "go/no-go" signals, down to digit and hand pose. McDonald et al. (2020) incorporated EMG into a control scheme for an upper arm device, capable of discerning intended wrist and forearm intent. Mendez et al. (2017) sought to evaluate the MYO EMG armband for its ability to distinguish hand poses but made no attempt to integrate it with a rehabilitative device, while work by Gailey et al. (2017) used an array of EMG electrodes, with some arbitrary and some targeted muscle location placement, to detect hand pose intent for use in control of a prosthetic hand. However, there have been limited studies into the feasibility of using low-cost EMG measurement arrays to detect residual muscle activations in impaired individuals.

1.3. Contributions

In the work by Rose and O'Malley (2019), keystrokes controlled the velocities of the motors acting in opposing motions of flexion and extension to move individual fingers as needed, which was sufficient for demonstrating basic efficacy of the SPAR Glove. To further investigate the glove's potential for assisting with ADL, the ability to command multiple desired poses in an intuitive manner is necessary. It is the goal of this manuscript to validate a proposed control scheme that uses the commercially available MYO armband as a low-cost wearable intent detection device for the requisite poses of the SPAR Glove. Whereas the use of EMG has been largely limited to simple agonist/antagonist pairs, as in the works of Cao and Zhang (2016) as well as Delph et al. (2013), this work seeks to generalize the use of EMG to distinguish between seven different poses which have been identified as useful for ADL. The outstanding question surrounding use of the SPAR Glove addressed by this manuscript is whether intent detection of the proposed grasp taxonomy is feasible using EMG with the SCI population.

To determine the feasibility of the proposed intent detection system, a validation experiment, discussed in Section 3.2, was performed with both able-bodied participants and participants with SCI. Participants wore the MYO EMG armband as they performed the goal poses to evaluate the classification accuracy of the intent detection algorithm operating in an offline mode. Motivated by the results of the validation experiment, a pilot study, discussed in 3.3, was conducted to evaluate classifier accuracy when detecting intent in real-time. The results of the validation experiment and pilot study are discussed in Section 5, and the manuscript's contributions are summarized in Section 6.

2. Myoelectric Interface for Intent Detection

2.1. SPAR Glove Actuation

The glove uses seven linear actuators (brushless DC motors (Maxon P/N 405794), planetary gear (4.4:1 reduction) and ball screw transmission (2 mm pitch, Maxon P/N 424222)), to retract tendons routed through Bowden cable transmissions. The Bowden cables terminate either in a palm bar (in the case of flexion tendons) or through hyperextension vertebrae (in the case of extension tendons). These components are labeled in Fig. 2. The resulting motions of the actuated degrees of freedom allow the SPAR glove to achieve seven distinct poses that have been shown to be useful in completing important ADL and enabling interaction with the user's environment. These poses were proposed by Dalley et al. (2011) and shown in Fig. 1 as those necessary to achieve a large portion of ADL with the use of a multi degree-of-freedom hand prosthesis.

2.2. Sensors

To detect user intent, the SPAR Glove possesses two flexible resistors mounted to the wrist via a fabric sleeve and 8 EMG sensors incorporated into the commercial off-the-shelf MYO armband. The goal of the sensors is to provide the user with multiple channels of input to control the assistive device. Though these flexible resistors do not play a part in the control scheme presented in this work, there is opportunity to further enhance the control algorithm by using them either as a triggering mechanism or to track compensatory movements.

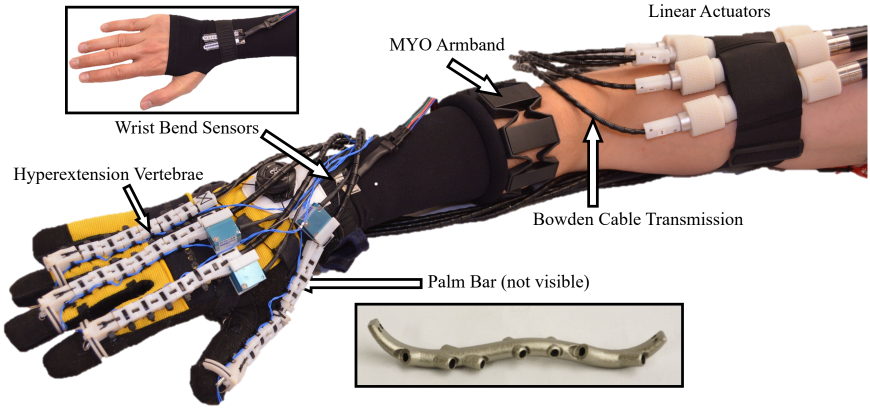

Figure 2. The SeptaPose Assistive and Rehabilitative (SPAR) Glove first proposed by Rose and O'Malley (2019) assists the seven pose taxonomy identified by Dalley et al. (2011). The combination of rigid materials such as the hyperextension vertebrae and palm bar, combined with the soft, fabric construction of the glove enable effective power transmission from the linear actuators without the bulk of fully rigid exoskeletons. The intended pose of the wearer is identified by classifying EMG signals captured by the MYO Armband. Further intent detection is possible through the use of bend sensors located at the wrist.

2.3. *Low-Level Control of the SPAR Glove*

The position of each actuator's ball screw is governed by a PD controller. The setpoints are defined in terms of the carriage positions along the lead screws and are commanded via a gearbox ratio defined within custom software developed at Rice University, the Mechatronics Engine & Library (Pezent and McDonald (2019)). In the current implementation, the commanded positions for each motor are selected from a table of setpoints based on the desired pose. When the command to move to a particular pose is sent, the setpoint for each motor is changed to reflect the motor's desired position in the applicable pose.

2.4. *User Interface for Control*

To convert the EMG signals captured by the MYO armband, the SPAR Glove uses a Linear Discriminant Analysis method that is based on the work of McDonald et al. (2020). In that work, researchers were interested in detecting EMG activity for control of a rehabilitation robot, and used EMG sensors placed directly over the muscle bellies for which activity was to be measured. The MYO armband works on a different principle, where electrodes may not be positioned over specific muscles. The algorithm computes a set of features from EMG data based on the foundational work of Hudgins et al. (1993). Those features are: the number of zero crossings (ZC), mean absolute value (MAV), waveform length (WL), number of slope sign changes, four coefficients (AR1, AR2, AR3, and AR4) of a fourth-order autoregressive model, and root mean square (RMS). The algorithm computes these nine features for each of the eight EMG channels of the MYO armband. These features are used to build a classifier unique to each set of sample input data. This functionality was built into the Mechatronics Engine & Library Pezent and McDonald (2019) as a set of tools for general use, and the tools can be adapted for the particular needs of the user. The algorithm is intended to be trained before each use, to account for differences in placement of sensors after donning the MYO.

The output of the classifier developed by McDonald can be utilized to represent the poses the wearer is intending. While the classifier can examine a moving window of data and issue a prediction, to improve the performance of the intent detection, the algorithm must cross a threshold number of predictions that must be reached prior to the device being actuated. The current implementation of the intent detection algorithm has a 1 second (1000 predictions) threshold that must be crossed prior to actuation. This introduces some delay into the user interface since an imperfect classifier will always take longer than 1 second to generate enough correct predictions to cross the threshold, but the increased reliability of the final movement is more important when interacting with objects in the physical world.

3. Experimental Validation of Intent Detection

To establish the performance of the MYO armband measurement and intent detection algorithm an experiment, described in Section 3.2, sought to determine whether the data generated by the MYO EMG armband is of sufficient quality to be reliably classified between the 7 goal poses. To separate any limitations arising from real-time implementation, this experiment classified data offline. A pilot study, described in Section 3.3, was explored whether the classification performance with the carefully segmented data from the validation experiment will translate to accurate classifications of live data.

3.1. Participants

The validation experiment collected data from both able-bodied participants and individuals with SCI, while the pilot study was done with SCI participants only. The able-bodied participants ranged in age from 22 to 35 years old, all were right handed and none claimed any physical or cognitive impairment. Three SCI participants, male, ranged in age between 42 and 65 years old, and right-handed prior to injury performed the validation experiment. Only two SCI participants (SCI 2 and SCI 3 from the validation experiment) performed the second experiment. All data collection was undertaken in compliance with the recommendations of the Institutional Review Board of Rice University, protocol 882515-1, with written informed consent obtained from all users.

Initial testing showed that the movements associated with the tasks were vigorous enough that the MYO tended to slip around on some of the participants' arms, particularly those with muscle atrophy. This phenomenon made training the classifier difficult since the EMG patterns changed every time the MYO lost contact with the skin. To correct for this problem, the participants donned a compression wrap on their forearms that surrounded the MYO and kept it from slipping and changing positions on the skin during testing.

3.2. Offline Classifier Accuracy in Able-Bodied and SCI Individuals

To determine whether the classifier can be used to successfully used to discriminate between the 7 goal poses, test participants were recruited to cycle their hands through the various goal poses and hold those poses for 4 seconds. The data were then parsed to isolate multiple segments of data and then saved data were used as sample sets to feed into the classifier. Each participant listened to a recorded set of instructions directing them to hold a particular goal pose for four seconds, then relax for two seconds in the neutral position shown in Fig. 3 before being given the next pose cue. Each participant performed each pose in this manner for 10 repetitions, providing a sufficient amount of data to both train the classifier and create data samples to feed into the classifier and test its efficacy.

Figure 3. Participant performs the reposition pose during data capture with the MYO armband. All participants remained in the pictured neutral pose for the EMG data collection with the MYO armband. The MYO was able to capture sufficient EMG activations even for participants who were unable to make the desired poses, as seen here.

The samples generated during the data-gathering exercise were parsed so that the time-series data showing muscle activation were separated from the data showing relaxation. To systematically separate the different pose generation sequences, the root mean square (RMS) of the raw time domain muscle activations were segmented with crossing a 10% threshold of max RMS identified as potential series start points. All eight EMG channels were segmented based on the channel that had the most even segmentation, that is, the largest minimum gap between these 10% threshold crossings. Once the “best" channel was determined, the edge placements were applied to all channels and data could be parsed into segments for use in the classifier. Since there was no distinction between the training data and the samples that were to be classified in the experiment, and to diversify the training data, the data were separated into a series of training and evaluation data sets. These sets consisted of every unique combination of 7 grasp sequences training data, with the remaining sequences classified.

3.3. Pilot Study: Online Classifier Accuracy

To expand on the validation experiment, a pilot study was conducted to explore the performance of the classifier in a real time implementation. As in the validation experiment, the classifier was provided with seven segmented samples for training each pose. However, instead of segmenting the data in a post-processing stage, the training set was manually captured in real time prior to the experiment, and not segmented further. Then, instead of the four second pose and two second rest periods from the validation experiment, the pilot study participants stepped through the seven goal poses, holding each pose for ten seconds before resting and moving to the next pose. Participants were not notified of the classifier’s output, to separate the wearer’s ability to modulate in response to biofeedback from the intent detection algorithm.

4. Results

The results of the validation experiment and pilot study show that the EMG signals captured by the MYO armband possess enough information to classify the seven goal poses, but there are still some limitations to the intent detection algorithm, especially for real-time implementation.

4.1. Offline Classification results

First, it is clear that the signals captured by the MYO armband are sufficient to classify the seven goal poses, as shown by the average confusion matrix for all able-bodied participants in Fig. 4.

Figure 4. Average Confusion Matrix for the offline classification of Able-Bodied participants EMG activations, with the intended pose along the horizontal axis, and the classifier’s output pose along the vertical. The high values along the diagonal show a strong performance for nearly all poses..

The results for the three participants with SCI are shown in Fig. 5. These results show similar performance to the able-bodied participants, but with some decreased classification accuracy for poses which are mainly differentiated by thumb position, such as the lateral pinch and hook.

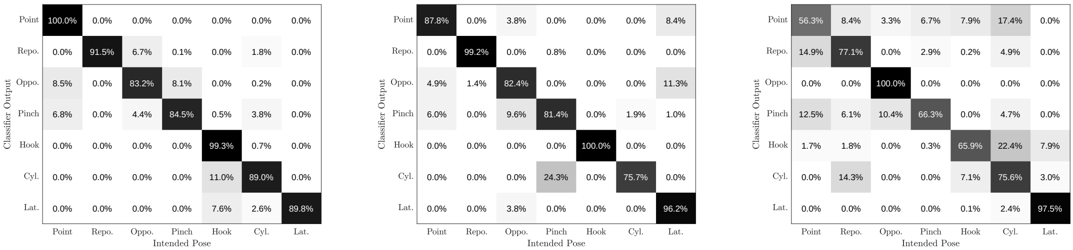

Figure 5. Confusion Matrices for the offline classification of SCI participants (1-3, from left to right), with intended pose on the horizontal axis and classified pose on the vertical axis. The high values along the diagonal show similar performance to the able-bodied participants. However, certain poses which are mainly differentiated by thumb opposition, such as the hook, cylindrical grasp, and lateral pinch, had lower performance..

An additional metric beyond the classification accuracy to consider is the confidence rating presented by the intent detection algorithm. This confidence represents the ‘distance’ between the classes, which increases the more separable the different classes are, normalized from 0-100%. The classifier selects the class with the highest confidence, and the accuracy of this selection is described in Fig. 4 and 5. The algorithm’s confidence in its classification can further explain the quality of the classification. These confidence values for able bodied subjects are presented in Fig. 6, which shows the confidence ratings for each classification averaged across able-bodied participants. Of particular note is that the main diagonal’s average confidences are typically near 90%, whereas the off-diagonal (incorrect) classifications hover closer to 50%, indicating that the classifier can indicate to the wearer and device that the classification is likely to be incorrect.

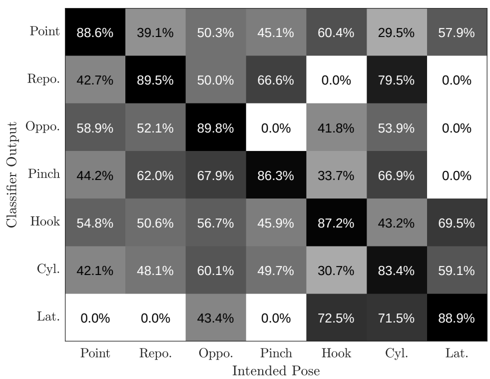

Figure 6. Average classifier confidence values for each classification for the offline classification of able-bodied participants EMG activations. The high confidence values along the diagonal are a representation of the separability of the trained classes and the classified data, which supports the use of the MYO and intent detection algorithm to classify the seven goal poses using forearm EMG measurements.

The average confidence values for the SCI participants are presented in Fig. 7. These results show high confidence for the first SCI participant, but decreased confidence values for the other two. Still, the diagonal (correct) classes typically had the highest confidences, further supporting the ability of our procedure to acquire data from the MYO and rely on the classifier to separate the EMG data into recognizable end goal poses.

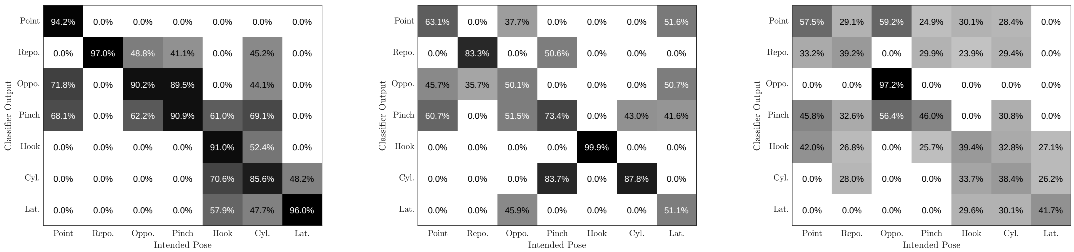

Figure 7. Average classifier confidence values for each classification for SCI participants, which show reduced performance as compared to able-bodied participants. However, the performance of the first participant (left) as well as the relatively high confidences for many of the diagonal (correct) values suggest that the proposed method still bears promise for use.

4.2. Pilot Real-Time Results

The results of the real-time tests for SCI participant 2 and 3 are shown in Figure 8. These values in the matrix reflect the percentage of the ten second period during which the classifier correctly identified the intended pose through the previously described threshold method.

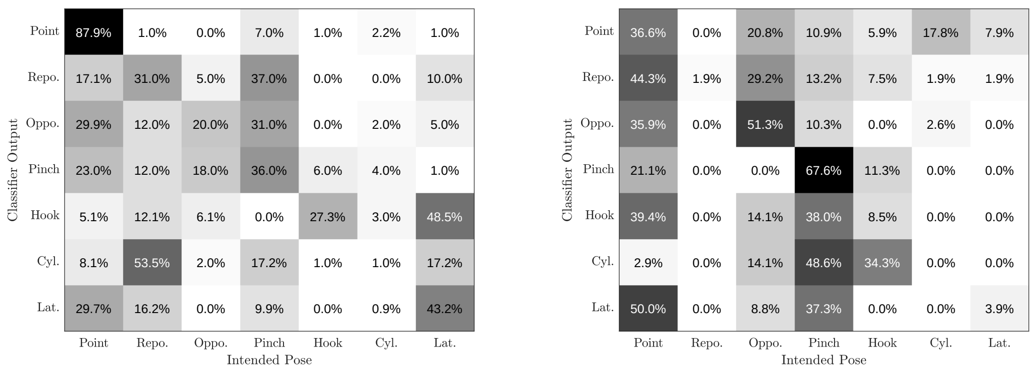

Figure 8. Confusion Matrices for SCI02 (left) and SCI03 (right) from the real time pilot study. The reduced performance likely arose from difficulties segmenting EMG data in real time, and identifies directions for future work.

5. Discussion

In general, the results from the validation experiment and pilot study suggest that the MYO armband, coupled with the proposed EMG classification algorithm, is capable of detecting user intent and accurately selecting the goal pose.

5.1. Intent Detection Algorithm's off-line Performance with Able-Bodied Participants

From the results it is clear that the majority of classifications in able-bodied participants are unambiguous when the data is carefully chosen, though not all poses are equally clear. For example, the poses which are only differentiated by thumb opposition, such as the cylindrical grasp and the lateral pinch, are sometimes incorrectly classified as the other. The confidence values for all poses, and these poses in particular, suggest a few interpretations. While it is possible that the particular training data used was insufficient to train the algorithm to separate the different classes, the other, more successfully-separated classes with high average confidences suggests that this is not the case. To improve the performance of this intent detection method, there are a few options. First, we could seek to increase the confidence with an additional EMG sensor at the thenar eminence to capture activations of the abductor pollicis brevis detect thumb opposition activations. Second, we could expand the algorithm to include input from another type of sensor, such as one of the bend sensors in the wrist, or another modality such as IMU to better predict the desired pose (Bennett and Goldfarb (2017)).

Third, we could reconsider the goal poses, and instead of trying exert effort to discern the difference between similar poses, focus on identifying other key aspects of the poses or different poses all together. Perhaps these poses, which were used to explore the DOF space are not well separable in the muscle activation space, and it would be more reasonable to train on a related, but slightly different taxonomy. The end goal would be to create a more separable set of activations which can control the glove. Such a set could consider activations to classify the four DOF from the original use of the taxonomy by Dalley et al. (2011), or even a more reduced set, relying on more passive constructions to open and close the fingers. Perhaps the easiest, and most robust option would be to have the algorithm consider its confidence when making decisions, and when the confidence is below a specified threshold, request confirmation or some other secondary 'check' on the intent detection.

5.2. Intent Detection Algorithm offline Performance with SCI participants

The classifications in SCI participants were more ambiguous than those of able-bodied participants. Some participants were unable to command their hands into the desired poses, but were still able to generate some muscle activations. Even with the reduce magnitude and quality of muscle activations, the confusion matrices generated by the classifications of SCI participants' activations demonstrates that classification is possible using only the EMG data from the MYO armband.

5.3. Real-time performance of intent detection algorithm

The reduced performance in the pilot study could be the result of a few factors. First, while the training data was of the same type as in the validation experiment, the evaluated data was changed for the pilot study to a 10 second stream to allow the classifier to make a series of predictions. While there is likely a difference between the EMG activations generated while initiating a pose from rest from those generated by holding a certain pose for able-bodied individuals, it is not clear if the same is true for impaired individuals who never reach the desired pose. It is also possible that the first-past-the-post interpretation of the classifier's output along with the lack of feedback provided to study participants contributed to some of the decrease in performance. In addition to feedback, further training with the MYO beyond the 15 minutes in this study could have resulted in improved performance. Lastly, the manually-captured training data, expected to be similar to a real-time implementation of the algorithm, may have been too coarsely segmented to provide a quality training set.

5.4. Future Work

As shown in the promising results of the validation experiment and the pilot study, there is tremendous opportunity for additional work with both the SPAR Glove and the intent detection algorithm. The area most ripe for fine-tuning is the live performance of the classifier, which has many parameters that may benefit from adjustment. The sample rate of the MYO defaults to 200 Hz, but that may actually be providing more information than the classifier requires. It would be interesting to throttle the information flow and observe the accuracy rate. There are times when the user may not be attempting to perform any action at all, but the nature of the prediction algorithm is such that it incorporates this "neutral data" into the window that the predictions are based on. Some additional strategies to force the classifier to look at only the relevant time window for a given motion may produce results more in line with the static data in the off-line validation. Additionally, the relative weights of the nine parameters (Section 2.4) used by the classifier could be adjusted to each participant, potentially improving the performance over the standard set used for all participants in the experiment and pilot study. The user interface could also incorporate a screen wherein the user could see a preview of the pose before confirming their intent. In this way the glove could be made to avoid responding to false predictions and constantly shifting between poses. The other sensors in the MYO may be leveraged here to provide additional input channels, specifically the IMU to act as either a triggering mechanism or as a way to account for compensatory movements which may be unique to each user.

6. Conclusion

This manuscript presented the details and experimental validation of the intent detection subsystem of the SPAR Glove, which uses a low-cost, wearable EMG system to detect the muscle activation patterns associated with one of seven goal poses. The accuracy rates for each able-bodied participant demonstrate the classifier's ability to recognize goal poses. There is a clear difference in the classifier's ability to correctly identify poses in the able-bodied versus the SCI population, but the data from the SCI participants demonstrate that classification is possible using only the data from the MYO armband. Future work aims to improve the performance of the proposed intent detection algorithm in a real-time implementation.

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Data Availability Statement. Data is available upon request to the corresponding author.

Conflicts of Interest. The authors declare none.

Ethical standards. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional guides on the care and use of laboratory animals. All experiments and the data collection were undertaken in compliance with the recommendations of the Institutional Review Board of Rice University, protocol 882515-1, with written informed consent obtained from all users.

Author contributions. J.E.B. and C.G.R. designed the study. J.E.B. abstracted the data, wrote the first draft, and approved the final version. C.G.R and M.K.O. revised the manuscript and approved the final version.

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