EMG Pattern Classification to Control a Hand Orthosis for Functional Grasp Assistance after Stroke

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Abstract— **Wearable orthoses can function both as assistive devices, which allow the user to live independently, and as rehabilitation devices, which allow the user to regain use of an impaired limb. To be fully wearable, such devices must have intuitive controls, and to improve quality of life, the device should enable the user to perform Activities of Daily Living. In this context, we explore the feasibility of using electromyography (EMG) signals to control a wearable exotendon device to enable pick and place tasks. We use an easy to don, commodity forearm EMG band with 8 sensors to create an EMG pattern classification control for an exotendon device. With this control, we are able to detect a user's intent to open, and can thus enable extension and pick and place tasks. In experiments with stroke survivors, we explore the accuracy of this control in both non-functional and functional tasks. Our results support the feasibility of developing wearable devices with intuitive controls which provide a functional context for rehabilitation.**

I. INTRODUCTION

Wearable devices are an attractive alternative to other robotic rehabilitation therapies that, traditionally, require therapist supervision provided in a clinical setting, and take place in a non-functional context. Therapy is more likely to be effective when training is distributed in smaller but more frequent aliquots [1] and when training includes performing actual Activities of Daily Living (ADLs) [2]. Wearable devices can provide both of these advantages.

For devices to be wearable in a functional context, they need intuitive, user-driven controls. We are developing an electromyography (EMG) controlled exoskeleton hand orthosis for stroke patients. This is a step toward user-controlled take-home orthotic devices to help perform functional tasks.

In previous work, we presented an exotendon orthosis - a soft glove with guided tendons driven by linear electric actuators to elicit desired movement patterns [3]. Here, we create and test a control mechanism for the exotendon device based on surface EMG. Fig. 1 shows this exotendon device, including the EMG armband which provides control input.

Our approach uses pattern classification - identifying patterns in EMG signals from the entire forearm - to determine user intention. In this study, we apply EMG pattern classification to determine the user's intention either to open or

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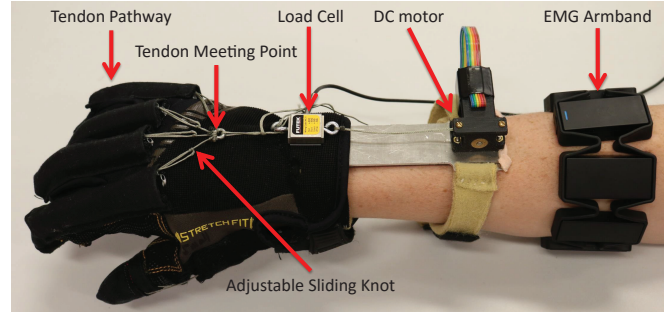[3]Co-Principal Investigators

Fig. 1. Prototype hand orthosis in extension configuration with EMG armband.

to close the hand, and use this signal to produce physical movement assisted by the orthosis. While we do not measure cognitive load, the short training sessions that enable the user to operate the device suggest that using signals from the same muscles that drive an unimpaired hand is an intuitive control mechanism for an orthosis. Overall, we present a complete mechanism comprising hardware and algorithms to:

- Detect a motor impaired user's intention to execute specific hand movements based on forearm EMG.
- Use an encapsulated commodity EMG sensing suite without needing precise sensor positioning. This is in contrast to medical grade EMG sensors placed on a specific muscle by a trained professional, which do not allow in-home use outside of direct medical supervision.
- Physically elicit the desired movement pattern in stroke patients. We do not study EMG in isolation: we combine the control with a real orthosis and show it enables functional grasping in our target population. The presence of the physical device alters the EMG data obtained during operation; our approach is designed to cope with this phenomenon.

To the best of our knowledge, no existing hand orthotic system has concurrently demonstrated all of these characteristics. The key to our approach is pattern classification, which enables the use of commodity EMG armbands. Commodity armbands have the potential to allow complete portability as well as user-directed, in-home use. *Pattern classification of functional movements for stroke subjects has so far not been studied in conjunction with a physical orthosis that enables grasping.* Our experience indicates it is important to study these components together, as we aim to progress towards fully user-driven execution of complete tasks.

II. RELATED WORK

Proposed control methods for orthoses include brain control interfaces [4], bilateral control [5], therapist/user driven

orthoses [6] and EMG control. In this study, we use an EMG-based control mechanism. This control method has been used successfully for orthoses of the knee [7], upper arm [8], and wrist [9], as well as the hand.

A number of proposed EMG controls for hand orthoses include the use of bilateral muscles [10] or bicep muscles [10], [11]. We have chosen to focus on ipsilateral muscles of the forearm, aiming for more intuitive control for the user, and also leaving the bilateral hand free to operate independently. Furthermore, most forearm muscles are used specifically to manipulate the hand, whereas bicep muscles are not.

Hand orthoses using ipsilateral forearm EMG controls are largely developed with either the goal of hand function improvement or grasp assistance [12]. A number of studies have shown the ability to process EMG data in order to predict hand position [13], [14], [15]; the armband we use to collect EMG signals has a similar built-in ability to extract hand control signals based on typical EMG patterns of a healthy user. None of the above studies, nor the armband, demonstrate the feasibility of using their control scheme in conjunction with an orthosis that enables the execution of functional tasks. Our experience indicates that methods which predict hand motions in absence of an orthosis need significant adaptation to be effective when an orthosis is present (Section IV-C). Our study presents a method for training the EMG control in the presence of an orthosis to better predict hand position while the orthosis is operating.

In EMG-driven controls that are developed with orthoses to enable functional tasks [16], [17], [18], 2 sensors are placed by trained experimenters on specific pairs of muscles. The control then uses a threshold to determine when to open and close the orthosis. Our control does not require placement on specific muscles to function, resulting in a much easier donning process. Our commodity sensors are fully encapsulated and wearable, with no separate amplification or power electronics. Both of these features are important for building wearable orthotics that patients will one day be able to use at home without direct medical supervision. Furthemore, instead of looking only at pairs of muscles and thresholding activation signals (as in the above studies), we investigate patterns within the EMG signal of the entire forearm. This allows for future development of the EMG control to include multiple and varied hand positions. It has been shown that pattern classification can identify multiple hand positions in stroke patients [19]; therefore, we predict our control approach will be able to grow and develop with our orthosis design as, in future studies, we continue to enable more hand positions in stroke patients.

As stated above, pattern classification of functional movements for stroke subjects has been studied with the ultimate goal of controlling an orthosis [19]. However, to our knowledge, this kind of classification has not been studied in conjunction with an orthosis that enables functional movements. Our experience indicates that EMG controls for stroke patients need to be developed in conjunction with orthoses. We explore the feasibility of using pattern classification while simultaneously using an orthosis to enable hand extension.

EMG control in the field of prosthetics is well documented and can provide insights for EMG control of orthotics. Proportional EMG control [20] and pattern recognition based EMG control [21] of prosthetics are paradigms also used in orthotics. Prosthetic EMG control of individual finger motions [22], [23] and prosthetic EMG control which determines force and grasp type [24] have been explored. Control optimization studies have informed both signal processing [25], [26] and control hierarchy [27] of prostheses.

In prosthetics, there is also the question of how to train the device to perform optimally. The 2 main approaches are system training and user training. System training is adapting the control to be more accurate and can involve gains, thresholds, computer-guided training or bilateral training to provide ground truth for the system [20]. User training is teaching the user to produce control signals that are easily distinguishable for the system and, in the context of EMG controls, involves teaching the user how to create consistent and distinguishable muscle patterns [21]. We believe that this latter approach can also prove valuable for the types of signals we use here, and plan to apply it in future iterations.

III. EXOTENDON DEVICE

Our EMG-based control approach is implemented and tested on a complete hand orthosis device, which we briefly describe here. In prior work, we presented a four fingered orthosis with two separate 1-degree of freedom (DOF) tendon configurations[3]. Here, we experiment with the configuration assisting with extension, often a difficult task for stroke patients because of the commonly observed impairment pattern of spasticity, which is excessive involuntary flexion. We chose to explore the prototype which enables extension because extension is essential for functional grasping. Extension is achieved by applying extension torques on the fingers through an exotendon network pulled by a DC motor.

Mechanical components are split into two modules: a forearm piece and a glove with a tendon network. The modules are connected via eyerings on both sides of the load cell (Futek, FSH00097) to facilitate donning (Fig. 1). With a therapist, donning takes approximately 5 minutes. The device weighs 135 grams.

The forearm piece is composed of an aluminum splint and a DC motor. The splint constrains wrist movement to efficiently transmit external torques to the fingers. The splint is angled either at 30 degrees, considered functional wrist pose [28], or at 0 degrees for the patients who cannot extend the wrist due to spasticity. A DC motor (Pololu corporation, 210:1 Low-Power Micro Metal Gearmotors) with a 15 mm/s maximum travel speed and a 80N peak force is mounted on the splint. Motor specifications are chosen to prevent dangerous tendon force levels without taking up space to improve wearability. A Proportional-Integral-Derivative (PID) position control is implemented to drive the motor. The motor's range of motion is determined at the beginning of clinical tests, depending on hand size.

The glove with a tendon network has tendons guided from the heads of the middle phalanges through raised pathways to

a meeting point on the back of the hand. The tendons on each finger are attached to a cloth ring on the middle phalanges rather than on the fingertips to avoid finger hyperextension. The tendons on all digits, except for the thumb, are routed on the dorsal side of the glove. The thumb needs a special routing scheme since it exhibits different movement patterns from the other digits; the thumb tendon is routed from the proximal phalanx head to the metacarpal joint, then wraps clockwise around the wrist to the eyering on the load cell. The tendons on all digits are tied with sliding adjustable knots to allow better fit for different finger lengths.

The DC motor which pulls the exotendon network is driven by the EMG-based control that is the main focus of this study. Once the EMG control determines the user's intention to open or close the hand, it sends a command to the DC motor mounted on the splint. The motor then extends or retracts the tendon network to allow the user to open or close the hand.

IV. EMG CONTROL

EMG patterns of the hemiparetic forearm are often altered after a stroke event [29]. This study is based on the assumption that these altered EMG patterns can still be used to control a hand orthosis; as control using forearm EMG sensors has a number of compelling characteristics. EMG-based control requires the same type of muscle activation as pre-stroke extension, which should make the control intuitive and place a low cognitive load on the user. Additionally, using ipsilateral EMG control leaves the other hand free to participate in the grasping task or to perform a different task.

Beyond altered signals however, EMG control of an orthosis for a stroke patient is difficult because of additional phenomena, such as spasticity and abnormal coactivation relationships between muscles [29]. As such, many orthoses that enable pick and place collect signals from only two muscles [16], [17], [18], with each muscle controlling a direction of the orthosis, often using a threshold based on the subject's maximum voluntary contraction. In these approaches, the subject must fully extend or close before the orthosis will move in the other direction. We aim to develop an exotendon device that responds immediately to a signal change from the control, throughout the range of motion of the user's hand. The user's ability to end extension allows more natural grasping for smaller objects as well as the option to change grasping tasks mid-motion.

One of the key tenets of our approach is to rely on signals from a multitude of sensors placed around the forearm. Unlike simple intensity thresholding, which is effective for a single sensor precisely located on a specific muscle, pattern classification identifies patterns in the complete set of signals from the sensors. This approach has three main benefits:

1) It enables the use of commodity sensors. Even though the quality of the EMG signal from commodity sensors is lower than medical grade sensors, we compensate for signal quality with sensor quantity. Pattern classification provides an image of the overall EMG signal in the entire forearm instead of trying to isolate a high quality signal from specific muscles.

2) It eliminates the need to search for specific muscles with exact sensor placement. Pattern recognition examines EMG signals from the entire forearm. Studies have suggested that when electrodes are placed around the entire forearm, targeted and untargeted placement of EMG electrodes result in similar classification accuracies [30]. Throughout our experiments, the only effort to position our EMG sensors was placing one of the sensors on the dorsal side of the arm. Even with this untargeted approach, we were still able to use pattern classification with good accuracy. The flexibility in sensor placement means that donning our control unit does not require a therapist, or even a basic understanding of forearm anatomy. For a device that is designed for take-home use in mind, this is an extremely desirable quality.

3) It allows for the possibility of an orthosis with more DOFs. Current orthoses look at two specific muscles, a flexor and an extensor. The flexor controls the close motion of the orthosis and the the extensor controls the open motion. Pattern classification allows for the recognition of more complex muscle motions, which could control different DOFs of the orthosis [21].

To acquire the EMG signal, we use the Myo Armband from Thalmic Labs. It has 8 EMG sensors and 8 IMUs, which can indicate the orientation and acceleration of the device. In this study, we only use the EMG sensors; however, the IMU sensors could be useful for future control iterations.

A. Pattern Classification

Our pattern classification algorithm seeks to take the 8-dimensional raw EMG data from the 8 Myo sensors and identify patterns that correspond to certain desired hand motions. Our current algorithm only identifies hand opening and closing, but we hope to incorporate more complex patterns into the classification scheme in future iterations.

We collect raw EMG data from the Myo Armband at a rate of 50Hz. At time t, we collect the EMG signals e_j^t from the sensors and assemble them into a data vector ψ_t:

$$\psi_t = (e_1^t \dots e_8^t) \tag{1}$$

We define the desired hand state at time t as $H_t \in \{O, C\}$, where $H_t = O$ corresponds to the intent to open the hand and $H_t = C$ is the intent to close the hand. While training, ground truth data H_t^g is provided by the experimenter who gives the subject verbal commands to open or close the hand. The training period is around 45 seconds - allowing the experimenter to command the user to try to open and close the hand twice. Although this training time is short, we receive a large quantity of data points (~2,400) which we use to establish patterns in the EMG with our classifier.

Raw EMG signals are used as the features for the classifier. Although many pattern classifiers require extraction of time-domain features, we receive our data at 50 Hz, so this would be impractical. Our results in Section V show our classifier

is robust enough that it does not need to extract time-domain features to classify intention with high accuracy.

Our first order goal is to predict H_t based on ψ_t (we will further process this result as explained in the next sections). We use a random forest classifier trained on the ground truth data described above to make this prediction. A random forest classifier is an ensemble machine learning method created from a combination of tree predictors [31]. Because of the random nature of the bootstrap sampling used to create our classifier, the number of decision trees in the forest classifier and the decision trees themselves change with every training iteration. Despite the underlying randomness, our classifiers for all subjects still achieve high accuracy.

We denote the random forest classifier function as:

$$CLAS(\psi_t) = p_t^O \in [0, 1] \qquad (2)$$

where p_t^O is the probability that $H_t = O$ (at time t, the user's intention is to open the hand). The converse probability that the user's intent is to close the hand is simply $p_t^C = 1 - p_t^O$. We filter and use this result as described in the next section.

B. Output Processing

We collect raw EMG data ψ_t at a rate of 50Hz. However, the time scale for hand opening and closing and for pick and place tasks is much lower frequency than the rate at which data is collected, so classifying individual data points correctly is not as crucial as correctly identifying a hand motion. To identify these motions, we assume hand posture does not change with high frequency, which allows us to filter and process the probabilities returned by the classifier.

While filtering raw EMG signals is a common technique, we chose instead to apply our filter to the results of the classifier. We compute filtered probabilities at time T as:

$$\hat{p}_T^O = \text{MEDIAN}(p_t^O), t \in [T - 0.5s, T] \qquad (3)$$
$$\hat{p}_T^C = \text{MEDIAN}(p_t^C), t \in [T - 0.5s, T] \qquad (4)$$

The 0.5s median filter increases transition delays, but helps eliminate spikes and spurious predictions. 0.5s was chosen because shorter filters resulted in spurious classification errors. Despite the delay, our subjects reported no noticeable delay between intention initiation and device movement. We note that, as a result of filtering, generally $\hat{p}_T^O + \hat{p}_T^C \neq 1$.

To produce the final output for our control, we compare $\hat{p}_T^O$ and $\hat{p}_T^C$ against two threshold levels, L^O and L^C respectively. If $\hat{p}_T^O \geq L^O$, then the controller issues an "open" command (retract the tendon). If $\hat{p}_T^C \geq L^C$, then the controller issues a "close" command (extend the tendon). If neither condition is met, no new command is issued and the orthosis continues executing the command from the previous step. The values of L^O and L^C are set manually by the experimenter for each subject after completing training data collection, then kept constant throughout all tests. The thresholds are set with subject feedback such that the control is responsive, but there are no spurious errors during sustained hand commands.

Device State	Subject Instruction		
	Open	Relax	Close
Tendon extended	O	C	C
Tendon retracting	O		C
Tendon retracted	O	C	C

TABLE I

TRAINING PROTOCOL AND ASSIGNED LABELS. FOR EACH COMBINATION OF INSTRUCTION GIVEN TO THE SUBJECT AND STATE OF THE EXOTENDON DEVICE, THE TABLE SHOWS THE GROUND TRUTH LABEL H_t^g ASSIGNED TO EMG DATA. TRAINING BEGINS WITH THE TENDON EXTENDED AND THE SUBJECT ASKED TO RELAX (TOP ROW, MIDDLE COLUMN) AND PROCEEDS IN COUNTER-CLOCKWISE FASHION.

C. Training with the Exotendon Device

The most straightforward method for generating training data to use with the classifier described above would be to simply instruct the user to attempt to open or close the hand, and label the resulting data accordingly. However, we quickly found that this simple procedure is flawed for multiple reasons. First, for stroke patients, we found that the default "relaxed" hand state (attempting to neither open nor close) still produces a strong, subject-specific EMG signal. The classifier would displayed a tendency to label this signal as either open or close, unless we provided explicit training data illustrating the difference. Second, we also found that physical interaction with the orthosis itself altered the EMG patterns: for the same user intention, signals recorded with the tendon fully retracted (assisting in hand opening) differed from those recorded with the tendon extended.

We address both of these issues through our training protocol and collection of labeled training data. Specifically, we design our training protocol as follows:

- We instruct the subject to attempt three hand poses: open, closed, and relaxed. For data collected during both closed and relaxed intents, we assign a ground truth label $H_t^g = C$, corresponding to a closed hand. Since our target population comprises patients with spasticity, this more closely mimics the subjects' natural state. This means that, for the orthosis to provide assistance, we must be detecting an active attempt by the user to open their hand. Being conservative in when to send a command to retract the tendon (and thus actively open the hand) reduces the risk of holding the hand open for longer than desired and causing discomfort. We note that one disadvantage is that continuous effort from the subject can lead to muscle fatigue, especially if the subject exerts great strain to provide an open signal.
- For all three user intents (open, close, relaxed) we collect training data in different states of the exotendon device, namely with the tendon fully extended, fully retracted, or moving between states. The training procedure is as follows. We instruct the subject to relax, with the tendon fully extended. We ask the subject to attempt to open the hand, with the tendon still fully extended. As the subject continues trying to open, the experimenter commands the tendon to retract, opening the hand. Once the tendon is fully retracted, we instruct

Subject	Age	MAS Extensor Score			MAS Flexor Score		
		Elbow	Wrist	Finger	Elbow	Wrist	Finger
A	60	2	1	1	2	2	2
B	39	1	0	0	2	3	3
C	80	0	0	1	1	0	2
D	66	2	0	0	2	2	1

the subject first to relax, then to attempt to close the hand. The experimenter then commands the tendon to extend, allowing the hand to close. Finally, the subject is told to relax. This procedure, and the ground truth labels assigned at every phase, are summarized in Table I.

The result of this training procedure is a labeled ground truth dataset covering combinations of user intent and device state. We use this dataset to train the classifier described above; at run time, the output of the classifier produces a command for the exotendon device as detailed in the previous section.

V. EXPERIMENTS AND RESULTS

Testing was performed with 4 stroke survivors, 1 female and 3 male. Subjects showed right side hemiparesis following a stroke event at least 2.5 years prior and had a spasticity level between 1 and 3 on the Modified Ashworth Scale (MAS). Table II shows clinical scores for all subjects. Testing was approved by the Columbia University Internal Review Board, and performed in a clinical setting under the supervision of Physical and/or Occupational Therapists.

We asked each subject to don the Myo and the exotendon device with the assistance of the supervising therapist. Training the EMG control as described in Section IV was performed for every session. The trained classifier was then used throughout the entire session. In real deployment, we would like the classifier to be robust enough to take the armband off and put it back on. We predict this is possible if the armband orientation on the forearm is consistent; however, this was not explored here because of the possibility of EMG patterns changing as the patient underwent rehabilitation. We aim to do this in future iterations of the control.

After training, each subject performed 4 experiments:

1) **EMG control without the device operating:** This experiment determined if the EMG signal in the hemiparetic forearm arm was strong enough to indicate the subject's intention to open or close. Without the device operating, there was little hand movement, but we still were able to determine the user's intention.

2) **EMG control with the device operating:** This experiment determined whether EMG control, in conjunction with our exotendon orthosis, could enable hand extension. With the device on, the Myo sends raw EMG signals to the classifier, which predicts intent and sends a command based on intent to the motor, which retracts or extends the tendon to move the hand and enable extension. Because this enables extension, it requires the training protocol described in Section IV. The subject's forearm was at rest on the table.

3) **EMG control during pick and place:** This experiment determined whether the exotendon device, in conjunction with EMG control, could enable pick and place. The exotendon device enabled hand extension but the forearm was no longer supported by the table.

4) **Button control during pick and place:** This experiment provided a baseline control comparison for the EMG control. A push button is attached to the device's motor and can be used to retract and extend the tendon. Pushing down and holding the button opens the glove until the hand is fully extended. Releasing the button at any point of the extend cycle causes the tendon to be released immediately and allows the hand to relax. The subject used the button with the non-affected hand to activate the device and complete pick and place tasks.

Experiments were performed at a pace comfortable for the subject and breaks were given between experiments.

Our result reports include two metrics: prediction accuracy and correctly predicted events. Prediction accuracy is defined as the percentage of individual data points ψ_t predicted by the classifier to be the same as ground truth. However, we believe that the more important metric is the ability to correctly execute a complete, meaningful hand motion, such as opening or closing. We attempt to capture this using the number of correctly predicted events. An event is defined as a change in intention signal, and a correctly predicted event means a predicted event which occurs within 850 ms of the ground truth event, with no incorrect classifications until the next event. The 850ms allowed for lag introduced by the median filter and allowed the subject intitate the action after a verbal command. Success for this metric was if the EMG control did as well as the baseline button control.

A. EMG control without the device operating

To collect the training set, the subject was asked to try to open and close the hemiparetic hand, with the understanding that the fingers likely would not extend, but that the EMG signal would change as different actions were attempted. (Note that this is the only condition in which we did not use the training protocol described in Section IV-C.) The testing set was collected in the same way as the training set. The subject's hand did not move, but the classifier was able to predict the subject's intention by the EMG signals.

The classifier for Subject A had an accuracy of 85.2% and correctly predicted 11 of 18 events. The intention for Subject B was predicted with 90.1% accuracy and 10 of 16 events were correctly predicted. The classifier for Subject C had an accuracy of 93.6% and correctly predicted 12 of 14 events. Subject D's intention was predicted with a 82.2% accuracy and 4 of 10 events were predicted. Fig. 2 shows ground truth, prediction results and non-thresholded filtered probability vs. time of Subject A, as well as the raw EMG which is classified. See Table III for a summary of the results.

B. EMG control with the device operating

In this section, the device was functioning to extend the hand, so training used the protocol from Section IV-C.
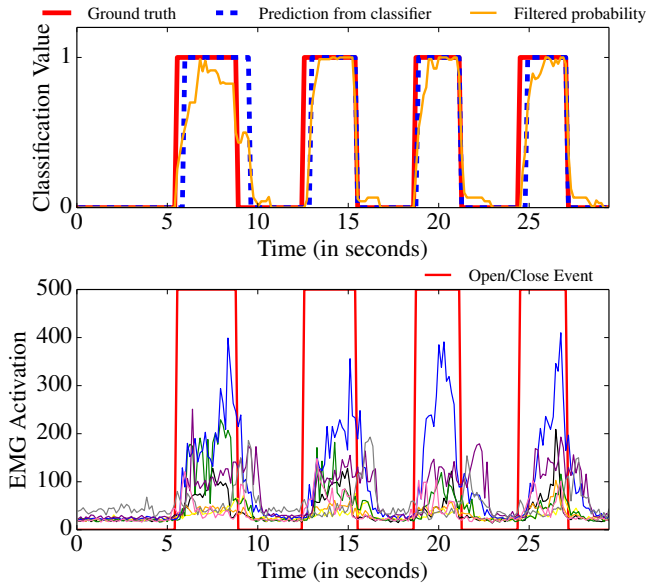
Fig. 2. **Top**: Prediction of classifier (dotted blue), ground truth (solid red) and filtered probability before thresholding (solid orange) vs. time for Subject A without the device operating. Classification value of 1: open intention, classification value of 0: no open intention. **Bottom**: Raw EMG of Subject A and open close events which correspond to the top graph.

TABLE III

RESULTS FOR NON-FUNCTIONAL MOTIONS

Subject	Without Device		With Device	
	% Accuracy	Correct Events	% Accuracy	Correct Events
A	85.2%	11/18	93.6%	16/18
B	90.1%	10/16	83.4%	4/16
C	93.6%	12/14	90.9%	9/11
D	82.2%	4/10	N/A	N/A

The testing set was collected as the subject was asked to try to open and relax the hemiparetic hand while resting the hand on the table. If the classifier detected the subject was attempting to open, the exotendon device would retract the tendon and the subject's hand would extend. If the intention to open was absent, the device allowed the hand to close.

Subject D was not included in these results because of subject fatigue. The classifier for Subject A had a prediction accuracy of 93.6% and correctly predicted 16 of 18 events. The classifier for Subject B had an accuracy of 83.4% and correctly predicted 4 of 16 events. Subject C had an accuracy of 90.9% and the classifier correctly identified 9 of 11 events. The finger flexor MAS score for Subject B was higher than for Subjects A and C. This could explain why Subject B's accuracy and correct event prediction are lower. An plot of the ground truth and the prediction results vs. time of Subject A, as well as the raw EMG which is classified, can be found in Fig. 3. See Table III for a summary of these results.

C. EMG control during pick and place

Precise ground truth is difficult to establish when the subject is performing pick and place tasks because an operator instructing the user when to begin and end extension would result in unintuitive grasping. Instead of percent accuracy, we use the number of correctly executed pick and place tasks as
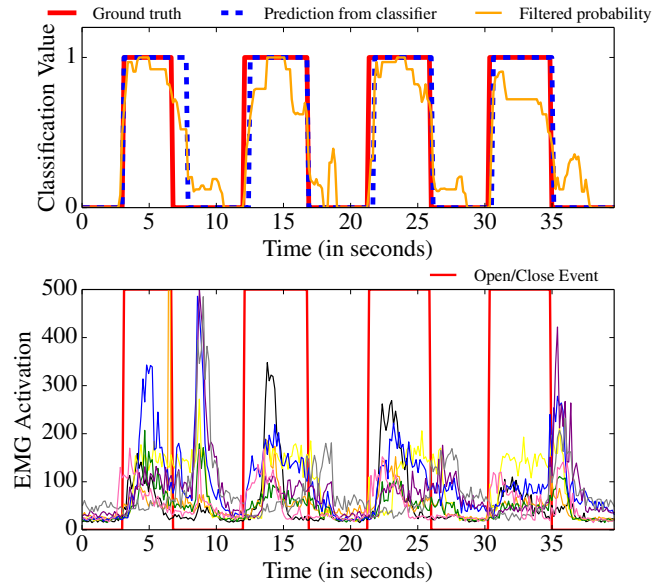

Fig. 3. **Top**: Prediction of classifier (dotted blue), ground truth (solid red) and filtered probability before thresholding (solid orange) vs. time for Subject A with the device operating. Classification value of 1: open intention, classification value of 0: no open intention. **Bottom**: Raw EMG of Subject A and open close events which correspond to the top graph.

TABLE IV

RESULTS FOR FUNCTIONAL MOTIONS (PICK AND PLACE)

Subject	Correct Events - EMG Control	Correct Events - Button Control
A	6/13	3/3
C	6/6	5/5

a metric for the pick and place experiments (both with EMG control and with button control).

We did not do additional training for this set, but used the classifier from the previous experiment.

During testing, the subject was asked to operate the exotendon device using EMG control to pick an object up, move it several inches, and then place it back down. The details of a complete pick and place motion, as well as the exotendon's role in the action are described in Fig. 4.

Subject B was not included because sizing issues rendered her unable to grasp objects. Due to subject fatigue, Subject D was also not included. Subject A successfully completed 6 of 13 pick and place attempts. Subject C completed 6 of 6 pick and place movements. We note that Subject C was higher functioning than the other subjects and was generally able to complete unassisted hand extension, albeit with significant difficulty. Nevertheless, the subject reported that the device provided assistance in hand opening during pick and place. See Table IV for a summary of the results.

D. Button control during pick and place

Before testing, the subject was instructed how to control the device using their left hand, and allowed to use the control for several minutes before performing pick and place tasks. During testing, the subject performed pick and place on the same object as during the EMG controlled experiment.

Again, Subjects B and D were not included in these results. Subject A successfully completed 3 of 3 pick and place
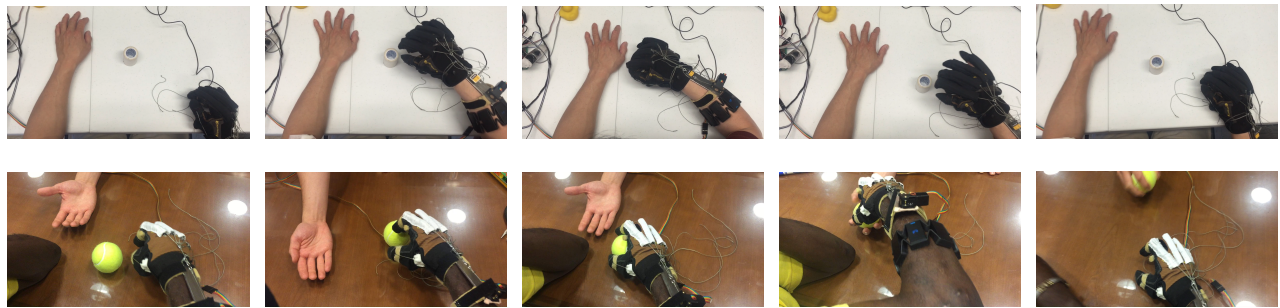
| Subject is at rest. The tendon begins in fully extended state and the hand is closed due to spasticity. | Subject begins grasp. The tendon retracts and the hand opens to enable grasping. | Subject grasps the object. The tendon extends to allow the hand to close over the object. | The subject releases the object. The tendon retracts to open the hand and to allow release of the object. | Grasp is complete and the subject is at rest. The tendon is fully extended. |

Fig. 4. Illustration of pick and place tasks by 2 subjects. Each row shows a complete task execution by one subject, progressing from left to right.
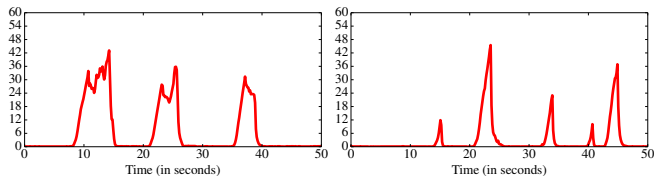
Force vs. time - button control.   Force vs. time - EMG control.

Fig. 5. Force results for Subject A - button control (left) and EMG control (right). Each peak corresponds to one hand extension for grasping.

attempts. Subject C successfully completed 5 of 5 pick and place attempts. See Table IV for a summary of the results.

E. Tendon Forces during Pick and Place Experiments

To assess the ability of the control to correctly interpret user intent, as well as the level of discomfort caused by operation, we measured the forces applied on the exotendon network during pick and place experiments. For the same subject, we compared peak forces obtained for EMG control versus button control. Our assumption was that an incorrect interpretation of a "close" signal, where the subject intended to close the hand but the assistive device did not react appropriately, would result in a spike in the force levels as the subject would be effectively fighting against the orthosis.

During the button controlled pick and place, the peak force on the tendon was 53.7N for Subject A and 58.6N for Subject C. During the EMG controlled pick and place, the peak force on the tendon was 59.6N for Subject A and 77.6N for Subject C. Fig. 5 shows an example plot of force vs. time during an EMG controlled and a button controlled experiment; each time series contains multiple hand extensions. We measured the forces using a load cell placed in series with the exotendon network. The peak force for the two controls showed little difference for Subject A, but for Subject C, EMG control lead to higher forces. However, there was enough variance between force peaks obtained with the same control mechanism to suggest that the difference could fall within normal operating range. Additional testing will be needed to further study this issue.

VI. DISCUSSION

Overall, our results showed effective pattern classification performance, to the level of physically enabling functional hand motion. Still, classification accuracy shows significant room for improvement. In particular, while the percent accuracy metric was consistently above 80% and often above 90%, the same level of performance was not achieved in the number of correctly predicted events. Most of the incorrectly predicted events were the result of the control not correctly recognizing the change in intention within the allowed 850ms window, rather than spikes caused by misclassification in the middle of the event. These delays were caused in part by the median filter, which uses the past 500ms to inform the control, thereby adding lag. Another possible cause was subject spasticity, which made it difficult for the subjects to relax or close after activating their extensor muscles.

Our results were trained and tested on separate data sets, both of which were taken from the same patient during the same session. We would like our trained classifiers to be robust enough to work for the same patient for different sessions. However, we believe it unlikely that pattern classification would work between different patients as EMG patterns between subjects are substantially different [19].

Pick and place experiments controlled by EMG showed lower accuracy than non-pick and place experiments where the device was operating. The difference between the 2 types of experiments was that in the former the subject's arm was engaged in the task, while in the latter the forearm was simply resting on the table. We hypothesize that, because of the stroke subjects' abnormal coactivation, a classifier which was trained while the forearm was resting on the table is confused by elbow extension during a grasping motion. We hope to compensate for this effect in future iterations by altering our training protocol to include training data both when the arm is resting and when the arm is extended.

As our work is eventually intended as a take-home device, the level of automation of the training is an important consideration. In this study, an operator was required to provide the training set with ground truth while instructing the patient to try to open or close. The operator also used the button control to implement the training protocol when required. In the future, the above responsibilities could be transferred to a user interface using visual cues instead of verbal commands, instructing the patient when to try to open and close, and programmed motor actions.

VII. Conclusions and Future Work

In this paper, we have shown that a EMG based pattern classification control of an exotendon device can enable functional movement in a stroke survivor. Our control achieves high accuracy during non-functional open and close hand motions, and can enable functional motions, like pick and place. The pattern classification technique allows the use of commodity devices which are easy to don, as there is no need to place sensors on specific muscles. Our control is intuitive and does not require an extended period of training. Our study shows that functional movement can be enabled by EMG control in wearable devices.

In the future, we would like to:

- Make our control robust to donning and doffing without having to take training sets each session.
- Make our control more robust to the abnormal coactivation initiated in stroke patients during functional tasks which require elbow extension.
- Include more hand movement patterns into the EMG classifier. We would like to differentiate between the 2 whole hand movement patterns of hand extension and of metacarpophalangeal (MCP) flexion / interphalangeal (IP) extension [3]. This would provide the user with functional motion assist for multiple types of grasps.
- Explore the idea of training users to produce movements which are more easily distinguishable for a classifier [21]. Although presented in the field of prosthetics, it would be useful for orthotics because abnormal coactivation in stroke patients makes classification difficult.

We hope that our control, and future iterations, will inform the development of a wearable orthosis that can be used outside of clinical settings.

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