

Multimodal Sensing and Interaction for a Robotic Hand Orthosis

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Abstract—Wearable robotic hand rehabilitation devices can allow greater freedom and flexibility than their workstation-like counterparts. However, the field is generally lacking effective methods by which the user can operate the device: such controls must be effective, intuitive and robust to the wide range of possible impairment patterns. Even when focusing on a specific condition, such as stroke, the variety of encountered upper limb impairment patterns means that a single sensing modality, such as electromyography (EMG), is not sufficient to enable controls for a broad range of users. To address this significant gap, we introduce a multimodal sensing and interaction paradigm for an active hand orthosis. In our proof-of-concept implementation, EMG is complemented by other sensing modalities, such as finger bend and contact pressure sensors. We propose multimodal interaction methods that utilize this sensory data as input, and show they can enable tasks for stroke survivors who exhibit different impairment patterns. We believe that robotic hand orthoses developed as multimodal sensory platforms with help address some of the key challenges in physical interaction with the user.

I. INTRODUCTION

Robotic devices for hand rehabilitation promise to alleviate some of the critical challenges of traditional rehabilitation paradigms. In particular, they could significantly increase the number of training exercises for cases where access to a therapist is limited. Recent advances [1], [2], [3], [4], [5], [6] have greatly improved the wearability of such orthoses: we now have devices that provide the needed actuation capabilities in a compact, wearable package, allowing greater freedom and flexibility than their workstation-like counterparts. Such wearable devices could allow use beyond the confines of a therapist's office.

However, the vision of a wearable orthotic device used for activities of daily living (ADLs) can only be realized if the patients are able to operate the device themselves. Control methods must be effective and intuitive, robust to long term operation, and cannot impose significant cognitive load. These algorithms must also cope with a wide range of impairment levels and abilities in the target population. While the actuation abilities of robotic hand orthoses have made great strides, control algorithms have not made similar progress in addressing these challenges.

The key to intuitive, user-driven control for a wearable orthosis lies in the ability to *infer the user's intent* from

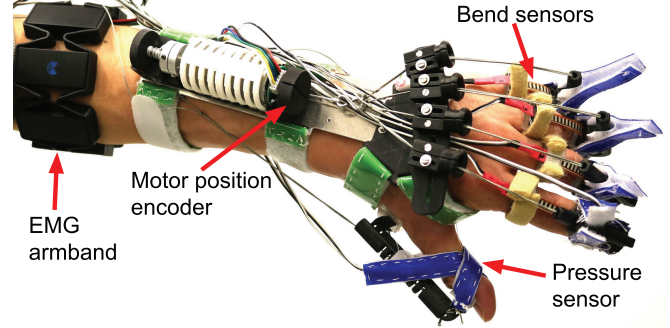


Fig. 1. Prototype of a hand orthotic device with multimodal sensors.

sensor data collected by the device. The robotic orthosis thus becomes a *sensory platform* in addition to an actuation mechanism. The control algorithm must infer the intent of the user from the collected data and respond with the appropriate actuation commands. In our own previous work, we developed a tendon-driven hand orthosis [1] that used a single sensing modality, forearm surface electromyography (EMG), to infer user intent [7]. Other studies (which we review in the next section) have also investigated EMG for control of wearable robotic devices.

While this body of work has shown that intuitive control is indeed possible, it has also highlighted numerous challenges. For example, EMG signals are inherently abnormal in hemiparesis and distorted by spasticity and fatigue. If signal patterns drift or change between training and deployment, the control method has no way of coping without new calibration or training data. Physical interaction with the orthosis also alters the signals. In fact, similar challenges face other interaction methods that rely on a single sensing modality: if the nature of the impairment (which varies greatly between individuals) is such that the signal exhibits too much or too little variation, the entire device can become unusable.

We were thus motivated to research and develop *multimodal sensing* for a wearable hand orthosis, where different sensing modalities can complement and augment each other. We believe that this general approach can help address some of the key challenges mentioned above for robust, intuitive user-driven operation. In this study, we aim for a proof-of-concept test of feasibility by introducing a concrete implementation developed for use by stroke patients.

While stroke subjects display a wide variety of impairment patterns, we have observed that many retain subtle, but consistent residual movements (e.g. partial extension of one or two fingers) or patterns of co-contraction that typically appear when a subject is prompted to open or close the hand. To measure these abilities, we outfit an extensor device with bend and pressure sensors. When EMG is insufficient

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to determine user intention, bend and pressure sensors can be used to control an orthosis. We refer to controls that use multiple sensor types for input as multimodal controls. The main contributions of this paper are:

- We develop an active hand orthosis as a multimodal sensory platform as well as an actuation device, allowing us to characterize physical interaction with the user in novel ways. In particular, we incorporate bend and pressure sensors into an exotendon framework with existing EMG sensing, without impacting grasping tasks, and keeping the orthosis compact.
- We introduce multimodal control methods for the orthosis, using the various sensors (EMG, bend, and pressure) as inputs. We then show that the different controls can be used with different impairment patterns commonly found in stroke subjects.

To the best of our knowledge, we are the first to propose intuitive multimodal control schemes which can be adapted to a variety of impairment patterns shown by stroke subjects. Pick and place experiments with two chronic stroke subjects with distinct impairment patterns confirm that such multimodal control is both feasible and effective, laying the foundation for further development in this direction.

II. RELATED WORK

EMG is one of the most popular unimodal controls for robotic hand orthoses because it requires relatively simple algorithms and enables intuitive operation. Most commonly, sensors are attached to the flexor and extensor muscles of the impaired arm and an open-loop control opens and closes the hand when the EMG exceeds a threshold [6], [8]. EMG pattern recognition algorithms are also becoming more popular, as they can classify multiple hand postures (as many as eight hand motions in stroke patients, if used with a select population because of abnormal muscle activation [9]) and enable the use of commodity EMG armbands [7].

Several strategies have been developed to adapt to these irregular EMG patterns. One strategy is to place the sensors on muscles which retain healthy EMG patterns. For example, stroke subjects can utilize the contralateral upper extremity [10] or facial expressions [11] to trigger EMG-based controls. Both of these methods require learning a control which uses muscles unrelated to the desired task.

An alternative strategy is to develop a multimodal control that uses EMG in addition to a more robust sensing modality. The VAEDA glove uses voice recognition to specify the control mode, and EMG signals to trigger commands [12]. Voice recognition is robust in ideal conditions, but sensitive to noisy environments. Radio frequency identification (RFID) tags on objects can serve as non-biological switches to identify desired hand postures, again using EMG as a trigger to execute these postures [13]. RFID tags predetermine which objects the subject can interact with, which limits their utility in real-world environments. Fusing mechanomyography (MMG) and EMG for prosthetic controls has been studied [14], [15], [16]. MMG is more robust to noise than EMG, but its use for stroke subjects is largely unexplored.

Other studies have developed controls which rely on types of sensors other than EMG. Some of these controls are unimodal - they trigger the device using a simple analog button [4], a bend sensor on the wrist [3], body-powered motions [17], or force myography [18]. The Soft Extra Muscle Glove uses force sensitive resistors (FSRs) as a control because they provide useful information when subjects interact with objects [19]. Zhao et al. [5] integrated optical strain sensors into a rehabilitation device based on pneumatic actuation in order to provide position feedback for control and motion analysis. However, unimodal controls have not yet been shown to be robust in execution of ADLs in non-controlled environment, or for long-term operation, and often rely on external cues, instead of natural hand motions.

Other works have developed multimodal controls using non-EMG sensors. For example, Steinkamp, et al. [20] use a 3D depth-camera and IMU sensors to analyze point clouds of the environment in order to classify appropriate hand assistance. Finally, some devices use sensors not as control inputs, but as tools to analyze hand movement. The SCRIPT passive orthosis is equipped with multimodal sensors to estimate joint rotations and torques. These sensing capabilities enable interactive rehabilitation games for users [21], [22], but use in real-life tasks or ADLs has not been attempted.

III. EXOTENDON DEVICE

To equip a hand orthosis with multimodal sensing, we expand upon our previous work with exotendon hand devices, specifically our work on tendon networks [1] combined with distal structures for efficient force transmission [23].

We developed a modularized device consisting of two parts, an aluminum forearm splint with actuation and 3D-printed fingertip components for cable routing [23]. The splint constrains wrist movement so that the motor forces are effectively transmitted to the fingers. For actuation, we use a Proportional-Integral-Derivative (PID) position controller whose range of motion is determined by user hand size.

On the distal end of the splint, there are adjustable tube components through which the exotendon network is routed. The angle and location of these tube components are customizable to enable better fit for each subject (Fig. 2a).

The 3D-printed fingertip components are secured to the fingertips using Velcro straps. The underside of the strap is rubber so the device will not migrate during use. The components route the exotendon network through a raised pathway. This pathway enhances force transmission efficiency by increasing the moment arm around the proximal interphalangeal (PIP) joints. In addition, the components prevent hyper-extension of the distal interphalangeal (DIP) joint and serve as an anchoring point for the tendon network.

The thumb moves differently than the other four fingers, and therefore requires different routing. As long as the four fingers are sufficiently extended, we can enable grasping tasks by simply splinting the thumb in a stationary, opposed position [24]. We splint the thumb using two tendon routes which adjust the thumb's abduction and extension (Fig. 2b).

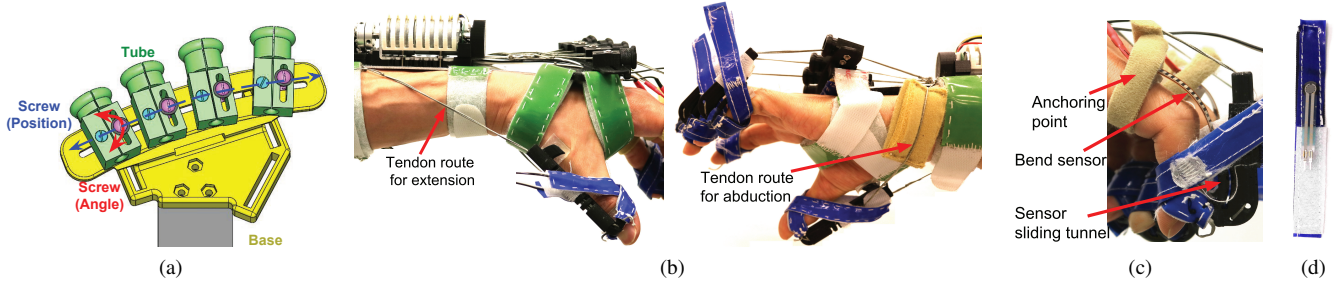


Fig. 2. (a) Top view of the distal end of the splint. Screws in blue determine position of the tube components. Screws in red tune angle of the tube components. (b) Routing for thumb extension and abduction (c) Integration of bend sensors. (d) Integration of pressure sensors in thumb straps.

IV. MULTIMODAL SENSING

While existing work has focused primarily on the role of robotic hand orthoses as actuation devices, we envision future devices serving an equally important role as sensory platforms, equipped to characterize physical interaction with the user. Numerous sensing modalities can be envisioned, focusing on tendons, joints, contacts, etc. In this context, we have developed a prototype of a multisensory platform for an orthosis, combining sensors for the following: forearm EMG, motor position, fingertip pressures, and joint angles (Fig. 1). Below, we describe the sensing modalities and how we incorporate them into the orthosis.

A. Forearm EMG

EMG is one of the most common orthotic controls because it is intuitive. EMG sensors are low profile, and commercial devices, like the one used in this work, are easy to don and doff. With relatively simple algorithms, EMG sensors can be used to identify a variety of different hand poses.

We use the Myo Armband from Thalmic labs for our EMG sensing. The armband consists of eight EMG sensors and is placed on the subject's forearm, proximal to the splint. Our pattern recognition algorithm (Section V-A) uses the EMG sensors to predict the user's intended hand state. Fig. 3a shows an example of EMG activation patterns as a subject attempts to open and close their affected hand. In this figure, the EMG activations for open and close are distinct; however, these patterns will change over time as the subject fatigues.

B. Motor Position

Motor position sensing is commonplace in robotic devices, and we include its description here for completeness. The motor encoder provides high-resolution position feedback, which enables us to control the actuator with position control and determine the current state of the orthosis. Because our tendon network is underactuated, this feedback does not provide information about individual finger behaviors, but their combined movement pattern.

C. Finger Joint Angles

Joint angles can serve as cues to determine patient intent. One typical pattern is partial voluntary movement, where patients try to open their hand and some fingers partially extend. Another, abnormal, movement pattern from which the sensing modality can potentially benefit is overactive stretch

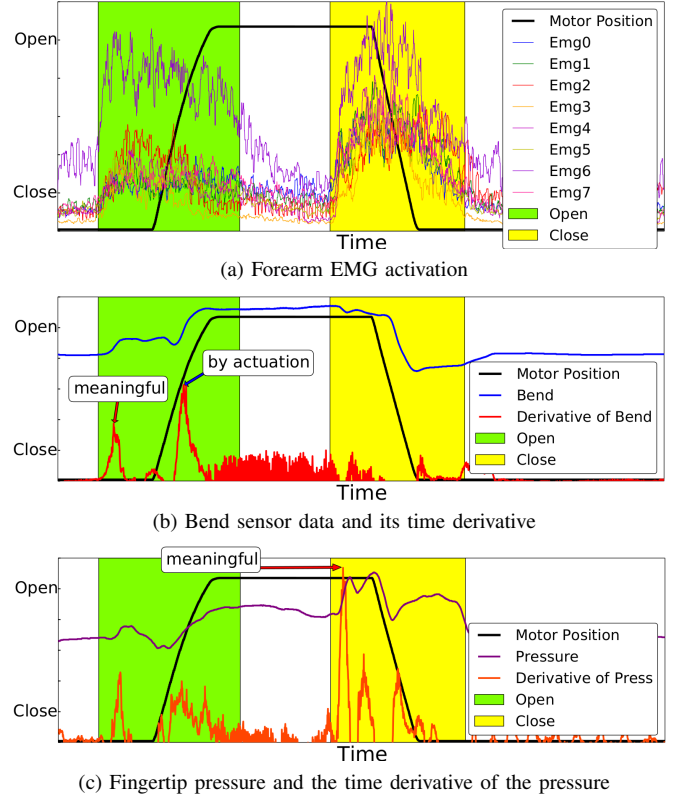


Fig. 3. Multimodal sensing data recorded while verbally instructing a user with stroke to open (green) and close (yellow) their affected hand during training. The plots depict the following sequence: the user, with hand at rest, is instructed to try to open the hand. After a few seconds, the device is also actuated to assist the open, shown on the plots by motor position. The user is asked to relax once the hand is in open state (tendon fully retracted). Then, the user is asked to try to close the hand despite resistance from the orthosis. Shortly after, the device extends, allowing the hand to close.

response [25]. This impairment pattern causes finger flexion when patients try to extend their fingers. By measuring PIP joint angles with bend sensors, both movement patterns can give us information about user intent.

We use a bend-sensitive resistor on each finger to measure joint flexion of the PIP joint (Fig. 2c). We assume residual movement of the PIP joint is greater than the MCP joint and therefore only deploy sensors on the PIP. For each finger, the proximal side of the sensor is anchored to the subject's proximal finger link by a strap. The distal side of the bend sensor is fed through a flat hole in the bottom of the fingertip component to keep it close to the distal link of the finger.

We found that using a simple threshold on the raw bend

sensor data to trigger an open command was limited as a control for functional tasks because motor position and the size of the objects with which the user interacts both dramatically affect the raw data values. Fig. 3b shows the raw bend data and bend derivative during an example open-close motion. Note that the bend derivative peaks soon after the subject is asked to open. The next notable maximum is caused by the device extending the fingers.

D. Fingertip Pressure

Pressure sensors on the fingertips serve a dual role: since the digit straps are the conduit by which exotendons apply force to the fingers, the pressure sensor can record the level of force between the hand and the device. When the user is performing a grasp, the pressure sensors will also record the contact force between the hand and the object. In this way, pressure sensing allows us to paint a complete picture of force transmission, from the orthosis to the patient's hand, and from the hand to the environment.

Fingertip pressure increases when the subject is either interacting with an object or trying to close the hand while the device is open. Though we cannot differentiate between the two actions, the increase in pressure gives us useful information about when the user intends to close their hand, especially when the user cannot maintain the muscle activation necessary to command the device to close.

Again, we use the time derivative of the pressure data rather than the raw data. As you can see in Fig. 3c, both the raw data and the pressure derivative increase soon after the subject is asked to close their hand, but the derivative provides more robust cues because the raw data alters over time due to fatigue and irregular tone. We only deployed the pressure sensors on the thumb, which is statically held in place, so actuation produces no notable changes in pressure.

We fit our exotendon device with pressure sensing using force sensitive resistors (FSRs). FSRs are compact enough for integration inside the digit straps which attach the 3D printed fingertip components to the subject's fingers. Fig. 2d shows how the FSRs are placed inside the digit straps.

For simplicity, we integrate pressure sensing only on the thumb because it is the finger which generates the greatest force when the subject tries to close their hand. The thumb is also used in all gross grasping, ensuring we will see interactions between the subject and any grasped objects.

V. CONTROLS

A. EMG Control

In previous work, we describe an EMG control which uses pattern recognition to predict user intention [7]. Here, we use the same eight sensor EMG armband (Myo) and a similar pattern recognition algorithm. Pattern recognition enables the use of commodity EMG devices, which are easier to don and doff than medical-grade sensors. Using pattern recognition, the EMG sensors do not need to be placed on specific muscles in order to identify user intention.

We place the EMG sensors on the subject's forearm, on the same arm as the exotendon device. Ipsilateral EMG control

harvests the EMG signal the user makes when they try to open or close their impaired hand, rather than requiring the user to learn an unrelated motion to control the device.

The algorithm we use for pattern recognition is described in our previous work [7]. The main difference in this work is that we aim to predict three possible user intentions rather than two: to open the hand (*Intent=Open*), to close the hand (*Intent=Closed*), and to relax (*Intent=Relaxed* - newly introduced here). The addition of the *Intent=Relaxed* class to our control allows the user to open the hand using the exotendon device, and then relax their hand while they are positioning their arm, for example in order to execute a pick and place task, without having to continue to exert effort to keep the hand open. We believe this approach can help avoid muscle fatigue.

To classify user intent at a given time, we input the EMG signals collected at that time into a random forest classifier and then a median filter. We compare the output probabilities to three manually set thresholds, and classify the end-result as belonging to either the *Intent=Open*, *Intent=Relaxed*, or *Intent=Closed* class.

The EMG control can then issue motor commands to the exotendon device based on the predicted user intention. If the EMG control predicts that the user's intention is *Intent=Open*, the device is commanded to open (retract the tendon, thus extending the fingers). If the user's intention is *Intent=Closed*, the device is commanded to close (extend the tendon, thus allowing the user to flex the fingers). If the predicted user intention is *Intent=Relaxed*, we continue to send the previous motor command to the device.

B. Multimodal Control

We propose two types of multimodal control. Subjects in our target population display a wide range of impairment patterns. Some cannot maintain a 'close' EMG signal, and others have more voluntary finger extension. A single sensing modality is limited due to the various impairment patterns; similarly, multimodal sensing is limited if it does not fit the subject's impairment pattern.

Our current exotendon prototype device is equipped with bend and pressure sensors. We propose one kind of multimodal control where bend sensors detect the user's intention to open the hand, and EMG sensors detect the user's intent to close the hand. The other multimodal approach uses pressure sensors to detect the user's intent to close the hand, and EMG sensors to detect the user's intent to open the hand. The multimodal approach which was chosen for each of our subjects was based on a qualitative analysis of their abilities, including their range of voluntary finger extension, and ability to maintain EMG signals.

1) *Bend to Open, EMG to Close*: The first multimodal control uses bend sensors to determine when the exotendon device should open, and EMG sensors determine when the device should close. Subjects who use this control would typically have the ability to initiate finger extension, but be unable to achieve functional extension and have difficulty maintaining an 'open' signal for EMG.

To determine user intent based on voluntary extension, we collect data from the four bend sensors built into the orthosis. In the current version, the therapist determines which of the subject's fingers has the greatest range of voluntary motion and we focus on bend data from that specific digit; in the future, we plan to integrate the data from all four sensors. Bend data is then passed through a moving mean filter with a window size of 0.25 s. Finally, we take the derivative of the resulting signal, which we refer to as $\frac{\partial b^i}{\partial t}$ (where the subscript i denotes the digit found to have the highest voluntary range of motion). Motor commands are sent as follows:

- When the orthosis is in the *Device=Closed* position (tendon extended allowing fingers to flex) and $\frac{\partial b^i}{\partial t}$ exceeds a given threshold L^B , the device is commanded to open (retract the tendon).
- When the orthosis is in the *Device=Open* position (tendon fully retracted, or motor stalled) and the EMG classifier predicts *Intent=Closed*, the device is commanded to close (extend the tendon).
- If neither of the above conditions are met, we continue to send the previous motor command to the device.

The threshold L^B is determined based on the training data collected in the procedure described in Section V-C. For the training dataset, we find the local maxima of $\frac{\partial b^i}{\partial t}$ while we ask the subject to try to open. We select the smallest value between the local maxima as L^B . If necessary, the experimenter will manually tune the threshold so the control can enable functional tasks. After the threshold is set, it is kept constant throughout all tests performed by the subject.

When the device is in the *Device=Closed* position, EMG signals are ignored, as are bend signals when the device is in the *Device=Open* position. Furthermore, our control will not switch motor commands while the device is transitioning from *Device=Open* to *Device=Closed* or from *Device=Closed* to *Device=Open*. We note that although this consideration can reduce rapid oscillations in the motor command, it is limiting if the subject only wants to open their hand halfway and then close again, for example, when grasping small objects. If the subject starts closing their hand before the motor is done transitioning, they will encounter resistance from the orthosis until the transition finishes and the control issues another command to the motor.

2) *EMG to Open, Pressure to Close*: For the second kind of multimodal control, EMG sensors determine when the exotendon device should open and the pressure sensors determine when the device should close. Subjects who use this control typically have a clear EMG muscle pattern for 'open' and difficulty maintaining a 'close' signal for EMG.

To implement this control, we use data from the thumb pressure sensor. As with bend data, the raw signal is first passed through a moving average filter with window size 0.25; we then compute the derivative of the output $\frac{\partial p}{\partial t}$. Motor commands are sent as follows:

- When the orthosis is in the *Device=Closed* position (tendon extended allowing fingers to flex) and the EMG classifier predicts *Intent=Open*, the device is

commanded to open (retract the tendon).

- When the orthosis is the *Device=Open* position (tendon fully retracted, or motor stalled) and $\frac{\partial p}{\partial t}$ exceeds a threshold level L^P , the device is commanded to close (extend the tendon).
- If neither of the above conditions are met, we continue to send the previous motor command to the device.

The threshold L^P is set with a procedure similar to the one previously described for the bend threshold L^B this time using training data while the subject is being asked to try to close. Again, we do not issue new commands while the device is transitioning between states.

C. Training with the Exotendon Device

Stroke subjects produce strong, subject specific EMG patterns which change dramatically depending on arm position, even if the subject's intention to open, relax or close the hand remains the same. These EMG patterns are further changed by the hand's physical interaction with the exotendon device. We therefore train the subjects with their arms in different positions and the exotendon device in different states.

We design our training protocol as follows: the exotendon device starts in the closed state (tendon is fully extended) and the subject is asked to relax. Then the subject is asked to try to open their hand. The experimenter waits three seconds, and as the user continues to try to open, the experimenter opens the exotendon device (retracts the tendon) to extend the subject's fingers. The subject continues to try to open for three seconds after the exotendon device is fully opened and is then instructed to relax. Next, the subject is instructed to close their hand. The experimenter waits three seconds and then closes the device. The subject continues to try and close for three seconds after the device has fully closed and then is instructed to relax again. During training, the experimenter provides ground truth to the program.

The subject repeats the above procedure five times. The first two times, the subject's arm rests on the table, and the next three times, the subject raises their arm off the table.

VI. EXPERIMENTS

We wish to evaluate the feasibility of our multimodal controllers when used by subjects with different impairment patterns, using EMG control as a baseline. We selected patients whose EMG patterns showed signs of being abnormal, affected by fatigue and interaction with the orthosis (which in our experience is commonplace), but who were still able to complete pick and place tasks using EMG control. Our multimodal control is designed to be robust to different types of impairment patterns, so we chose subjects with distinct impairments. In this work, the experimenter selected the appropriate multimodal mode, but we would like to explore making this selection automatic in future work.

Testing was performed on two subjects with chronic stroke. Both subjects were female, one presenting with right side hemiparesis and the other presenting with left side hemiparesis. Subjects had a spasticity level of two or less on the Modified Ashworth Scale (MAS). Both participants had prior

experience with the exotendon device, in varying capacities. Subjects gave informed consent and all testing was approved by the Columbia University Internal Review Board, and performed in a clinical setting under the supervision of an occupational therapist.

The experimenter placed the orthosis on the subject's hand and made any necessary sizing adjustments. The subjects were trained using the protocol described in Section V-C.

After training, we asked the subject to perform several open and close motions in order to compare the accuracy of the baseline and proposed controls. The experimenter verbally cued the subject open and close their hand while providing the program with ground truth for the desired motor command.

We also designed a pick and place task to evaluate the feasibility of the proposed control in a functional context: five blocks (2.54 cm square cubes) were placed in a square pan (2.94 x 2.94 x 3.05 cm) on a table in front of the subject. The supervising therapist instructed the subject to pick up the five blocks one at a time and place them outside of the pan as quickly as possible. The therapist timed how long it took the subject to pick and place each of the blocks. The subject was required to start with their hand in a relaxed state, grasp a block, transport it over the median with control and release it onto the tabletop. The task was considered complete when the subject released the block and activated the device to extend the digits. Grasps and releases which were performed without the proper assistance of the device were not counted.

We chose to design our own pick and place task, rather than use the Action Research Arm Test (ARAT) or Box and Blocks [26] because these tests evaluate both hand and arm function. Our device only affects hand function, so our experiment is designed to eliminate as many external factors relating to shoulder and elbow motion as possible.

For both the multimodal and EMG controls, the subject performed the above pick and place task three times. The subject was given three minutes of play time to acclimate to each control. Subject A performed three pick and places with the EMG control and then three pick and places with the multimodal control. Between tasks, she received a 2.5 minute break and after switching controls, she received a 5 minute break. Subject B was more susceptible to fatigue and had less training with the device. As such, training effect and the effect of fatigue were both more of a concern than with Subject A. To combat these effects, Subject B performed her six pick and place tasks alternating multimodal and EMG controls. She was given three minute breaks between tasks. Subject A used the 'press to close and EMG to open' multimodal control. Subject B used the 'bend to open and EMG to close' multimodal control.

We also asked Subject B to perform the pick and place tasks while wearing an arm support system, which uses gravity compensation to allow the subject to move their arm more easily. In stroke subjects, fatigue and abnormal coactivation relationships between muscles [27] can cause EMG patterns to change over time. The arm support system combats both these effects. Testing with and without the

arm support system helps us evaluate when the multimodal control is effective. Because fatigue was not a concern while wearing the arm support, Subject B performed the tasks using the same protocol as Subject A - three pick and place tasks with the multimodal control first, a five minute break, and then three pick and place tasks with the EMG control.

During testing, subjects were unaware of the type of control they were using. We wish the controls to be as intuitive as possible so subjects were merely instructed to try to open and close their hand.

A. Open-Close Motion Results

We compare the output of the EMG and multimodal controls to the ground truth provided by the experimenter during open and close hand motions. We report the global accuracy, the positive predictive value (PPV), and the negative predictive value (NPV) for our classifiers [28]. It has been shown that global accuracy can be misleading for EMG pattern recognition controls [28], so we believe another important metric is the ability to correctly identify transitions between motor commands. A transition is defined as a change in motor command, and a correctly identified transition means a predicted transition which occurs within 1.5 seconds of the ground truth transition. 1.5 seconds allows enough time for the experimenter to give the verbal command and for the subject to react and start performing the motion. We found that the subjects would often raise their arm off the table before they attempted the instructed hand motion, which increased reaction time significantly. We also report the number of false positive transitions, or transitions which do not have a corresponding ground truth transition. These falsely predicted transitions cause the motor to oscillate, confusing and frustrating the user. Success for our transition metrics is when the number of correctly identified transitions is close or equal to the total number of transitions and the number of false transitions is close to zero.

The results for Subjects A and B are shown in Table I. For Subject A, the multimodal control has a 4.2% higher global accuracy than the EMG control and is able to correctly identify three more transitions within the given time window. However, the EMG control has four fewer false positive transitions. For Subject B, without arm support, the multimodal control performed with 9.5% higher global accuracy and correctly identified two more transitions than the EMG control. With arm support, the multimodal and EMG control performed about the same, but the EMG control incorrectly predicted four more false positive transitions. Figure 4 shows the motor commands generated by the different controls and the ground truth provided by the experimenter for an example open-close motion performed by Subject B without arm support.

B. Pick and Place Results

For the pick and place testing, we timed how long it took for the subjects to pick and place each block. Results are reported as time to pick and place each block, averaged across three trials, along with the standard error (Table I).

		Open Close Motion Results					Time to Pick and Place					
Control Type		Global Accuracy	Transitions				Block 1	Block 2	Block 3	Block 4	Block 5	Total
			PPV	NPV	Correct	False Positive						
Subject A	EMG	72.8%	64.2%	78.4%	2/8	2	92.1±33.0	33.4±17.2	30.4±7.0	71.2±22.3	38.6±10.8	265.7±40.8
	Multimodal	77.0%	72.0%	79.9%	5/8	6	38.1±14.7	46.7±14.1	44.1±8.5	16.9±2.1	45.3±18.3	191.1±20.4
Subject B - no arm support	EMG	77.9%	85.4%	72.7%	6/8	0	12.7±1.5	9.1±0.6	14.3±3.0	17.8±5.1	13.0±3.8	66.8±5.6
	Multimodal	87.4%	85.5%	89.6%	8/8	0	11.4±0.3	14.5±3.4	10.0±1.1	16.7±3.8	25.7±12.9	78.4±8.4
Subject B - with arm support	EMG	85.8%	86.8%	84.7%	12/12	4	8.1±1.2	5.9±0.3	6.2±1.6	8.2±1.8	7.4±0.9	35.7±2.8
	Multimodal	86.8%	87.7%	86.4%	12/12	0	15.6±2.3	8.6±0.3	8.0±0.5	11.1±2.6	8.7±0.5	52.0±2.6

TABLE I
RESULTS FOR OPEN-CLOSE MOTIONS AND PICK AND PLACE TASKS.

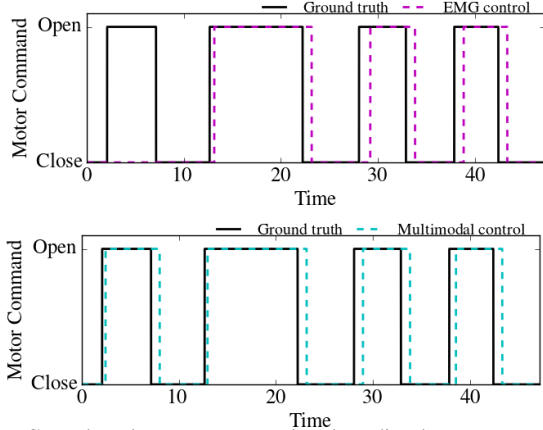


Fig. 4. Ground truth motor command and predicted motor commands generated by the EMG (top) and multimodal (bottom) control algorithms during an example open-close motion for Subject B without arm support.

On average, the multimodal control allowed Subject A to pick and place blocks 14.9 seconds faster and to complete the entire task 74.6 seconds faster than the EMG control. Subject B took longer with the multimodal control than with the EMG control, on average 2.3 seconds longer for individual blocks and 11.5 seconds longer the entire task without arm support, and on average 3.3 seconds longer for individual blocks and 16.3 seconds for the entire task with arm support.

VII. DISCUSSION

Our experiments show that the proposed multimodal control can be effective for subjects with a variety of different impairment patterns. Subject A has almost no voluntary extension in her fingers and has difficulty maintaining a ‘close’ EMG signal. On the other hand, Subject B can extend her fingers partially, but has a hard time maintaining an EMG signal for ‘open’. Our multimodal control can be customized to these different impairment patterns and enables open-close motions and pick and place tasks for both subjects.

For the open and close motions, the multimodal control often outperformed the EMG control. For both subjects, the global accuracy, PPV, NPV, and the number of correctly identified transitions within the given time window were all higher for the multimodal control than for the EMG control. The EMG control only outperformed the multimodal control in the number of false positive transitions predicted for Subject A: the EMG control had four fewer false positive transitions than the multimodal control and therefore fewer unnecessary motor oscillations.

Without arm support, Subject B finds it difficult to maintain or initiate an ‘open’ EMG signal and therefore the EMG control has a NPV which is 12.7% lower than the PPV. With the arm support, the PPV and the NPV are within 2% of each other. We hypothesize that the arm support relieves abnormal muscle coactivation experienced by the subject, and that when this coactivation diminished, the subject had an easier time maintaining an ‘open’ EMG signal, which increased the NPV. The testing conditions with and without arm support serve to illustrate just how varied post-stroke impairment patterns can be. The same EMG control had a 12% difference in NPV when we started providing arm support. Such a significant change in the performance of a subject-driven control for the same patient underlines the need for controls which can adapt to a wide range of impairment patterns, both between patients and as subjects undergo rehabilitation.

The pick and place results show that the proposed multimodal control is effective. For some subjects, like Subject A, it is more effective than EMG control, enabling the subject to complete pick and place tasks over a minute faster. For other subjects, like Subject B, EMG control is more effective. Although the EMG control was better for Subject B, the multimodal control was still effective. If used on a subject with an impairment similar to Subject B’s, but who had less distinct EMG, the multimodal control could still work.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we incorporate EMG, bend, and pressure sensors into an exotendon framework to create a multimodal sensing and interaction platform for a hand orthosis. We believe the future of robust controls for orthoses involves multiple sensing modalities which complement each other to inform controls. The bend and pressure sensors give us information about user intent if subjects display certain impairment patterns we have observed in many stroke patients.

We propose two multimodal control modes in this work, tailored to the different impairment patterns we have observed. Controls that can cope with many impairment patterns are necessary because these patterns vary across subjects; one patient could even display several patterns as they undergo therapy post-stroke. This is a preliminary study with a limited sample size; however, our results show that multimodal controls can be adapted to different impairment patterns and can enable both functional and non-functional tasks. This is a first step towards the development of robust, flexible controls, which could play an important part in

deploying robotic rehabilitation to a large population of stroke patients.

In the future, we would like to add more sensing modalities to our device, such as bend sensors on the MCP joints and IMU sensors to provide information about finger positions. IMUs and bend sensors have different limitations and strengths and will complement each other to jointly characterize finger movement. We also believe that a multimodal sensing platform, like the one developed here, could use its sensors not only for control, but also to track subject progress and rehabilitation. This will enhance our understanding of phenomena such as muscle spasticity and abnormal muscle synergies. It could also help us understand how impairment patterns develop over time as patients undergo rehabilitation.

To expand our study of robust multimodal controls, in the future, we would like to develop a control which uses inputs from all sensor types simultaneously, rather than use one type of sensor to open the device and another type of sensor to close the device. We believe that the future of these multimodal controls lies in the sensors' ability to complement and augment each other, and that such a control can continuously adapt and learn to predict user intent. For example, even when EMG control enabled pick and place tasks faster than the multimodal control, we noted that multimodal control can often predict signals that the EMG-only classifier misses (e.g. the first open-close motion in Fig. 4). This suggests that our multimodal control could be used to continue training the EMG classifier during real-time operations. Such continuous adaptation will also play an important role as the field transitions from controlled sessions to in-home environments.

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