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A Robotic Exoskeleton for Rehabilitation and Assessment of the Upper Limb Following Incomplete Spinal Cord Injury

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***Abstract*— Robotic devices have been shown to be efficacious in the delivery of therapy to treat upper limb motor impairment following stroke. However, the application of this technology to other types of neurological injury has been limited to case studies. In this paper, we present a multi degree of freedom robotic exoskeleton, the MAHI Exo II, intended for rehabilitation of the upper limb following incomplete spinal cord injury (SCI). We present details about the MAHI Exo II and initial findings from a clinical evaluation of the device with eight subjects with incomplete SCI who completed a multi-session training protocol. Clinical assessments show significant gains when comparing pre- and post-training performance in functional tasks. This paper explores a range of robotic measures capturing movement quality and smoothness that may be useful in tracking performance, providing as feedback to the subject, or incorporating into an adaptive training protocol. Advantages and disadvantages of the various investigated measures are discussed with regard to the type of movement segmentation that can be applied to the data collected during unassisted movements where the robot is backdriven and encoder data is recorded for post-processing.**

***Index Terms*— exoskeleton, robotic rehabilitation, physical human-robot interaction, spinal cord injury**

I. Introduction

Spinal cord injury (SCI) is a widespread issue in the United States with approximately 12,000 new cases occurring annually. In addition to the loss in quality of life among those affected, the direct and indirect costs associated with these injuries are estimated at about $20 billion per year [1]. One of the most significant factors which affects an individual's daily life after an incomplete SCI is the decrease in function of the upper extremities [2]. Therefore, regaining and improving use of the upper limbs is a critical part of SCI rehabilitation. Robotic rehabilitation has been shown to be a potentially viable method for rehabilitation of motor impairment in incomplete SCI subjects in a few case studies [3], [4]. The precision and repeatability of robotic devices may enable therapists to provide more targeted and effective rehabilitation. An additional advantage of robotic devices is that they can precisely gather and accurately record movement data during the training. The gathered data can be post-processed for objective and quantitative assessment of the subject's performance. In contrast, a physical or occupational therapist must generally rely on task-based assessments such as the Action Research Arm Test (ARAT), and Jebsen Taylor Hand Function Test (JTHFT) assessments. While these assessments are effective for determining movement ability relevant to activities of daily living (ADL), they are subjective and lack the precision to allow fine quantification of movement quality.

The effectiveness of upper limb robotic training for individuals with incomplete SCI has been investigated in a number of small-scale pilot studies. In Eng et. al, one subject used a wrist-forearm exoskeletal device [5]. The kinematic data collected via the robotic device were used to demonstrate the development in the subject's movement quality by investigating the change in movement variability. In another single-case study, Yozbatiran et. al employed an elbow-forearm-wrist exoskeletal device [4]. The feasibility, safety and effectiveness of robotic-assisted training of upper limb was demonstrated via evaluation of clinical performance measures of the subject, such as ARAT, JTHFT and the American Spinal Injury Association (ASIA) Impairment Scale upper extremity motor score, gathered before and after the twelve session protocol. In a more recent study, Pehlivan et. al validated a forearm-wrist exoskeletal device via a single-case study [3]. The outcomes of both clinical and robotic measures supported the hypothesis that intensive upper limb robotic rehabilitation would show beneficial outcomes. In each of these studies the number of subjects was extremely limited, and strong conclusions about the general applicability and efficacy of upper limb robotic rehabilitation in populations with incomplete SCI remains to be demonstrated.

Towards the use of robotic devices for assessment in upper-limb robotic rehabilitation, our own group has investigated the use of speed and smoothness metrics for subjects with stroke, but we have not applied this approach to other neurological impairments [6]. Zariffa et. al investigated the relationship between robotic measures and clinical measures in a study with twelve subjects with cervical level SCI. The authors found high predictability of clinical measures, which are directly dependent on ROM, grip ability, or movement smoothness, via robotic data, and concluded that robotic rehabilitation sessions can provide useful diagnostic information without the need for additional time or personnel resources [7]. Their study leveraged the sensing capabilities of the Armeo Spring for objective assessment.

In this paper, we present the MAHI Exo II, a robotic exoskeleton that targets the human elbow, forearm, and wrist joints in order to improve the distal dexterity essential to activities of daily living (ADL). We describe a clinical study

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TABLE I

ACHIEVABLE JOINT RANGES OF MOTION (ROM) AND MAXIMUM CONTINUOUS JOINT TORQUE OUTPUT VALUES FOR MAHI EXO II.THE VALUES GIVEN IN PARENTHESES IN THE TORQUE COLUMN SHOW THE CAPABILITY OF THE MAHI EXO I DESIGN. THE REQUIRED ROM AND TORQUE VALUES FOR 19 ADLS AS EXTRACTED FROM [8] ARE ALSO GIVEN FOR COMPARISON.

Joint	**ADL**		**MAHI Exo II**	
	ROM (deg)	Torque (Nm)	ROM (deg)	Torque (Nm)
Elbow Flexion/Extension	150	0.06	105	11.61
Forearm Pronation/Supination	150	0.06	180	2.30
Wrist Flexion/Extension	115	0.35	72	1.67
Wrist Radial/Ulnar Dev.	70	0.35	72	1.93

TABLE II

MAHI EXO II DEVICE CHARACTERISTICS

Joint	**Static Friction**	**Inertia**	**Viscous Coeff.**	**CL Position Bandwidth**
	(N·m)	($kg{\cdot}m^2$)	($\frac{Nm{\cdot}s}{rad}$)	(Hz)
Elbow Flexion/Extension	0.912	0.347	0.238	2.1
Forearm Pronation/Supination	0.1109	0.0258	0.0112	4.1
Wrist Flexion/Extension	0.1915	0.0032	0.0161	11.5
Wrist Radial/Ulnar Deviation	0.1759	0.0038	0.0059	12.3

designed to investigate the outcomes of robotic rehabilitation for subjects with chronic incomplete SCI. Specifically, we explore quantitative performance measures that are well-established in the literature to capture movement smoothness and quality. The strengths and weaknesses of the measures are discussed in the context of SCI rehabilitation. We also support our results with clinical outcome measures. The paper is structured as follows: Section II describes the MAHI Exo II, a wrist, forearm and elbow exoskeleton. Section III explains the methodology of the clinical study, and performance measures for both robotic and clinical data. Section IV presents the results and their implications. Conclusions are summarized in Section V.

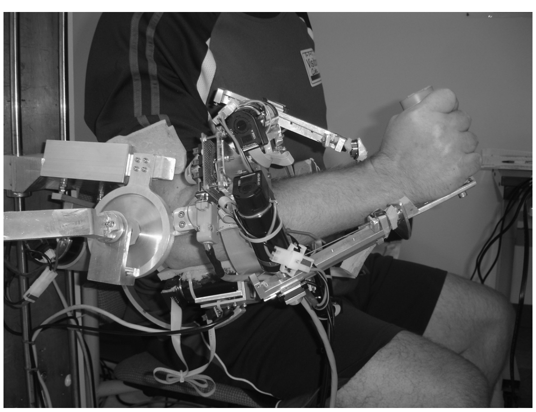

Fig. 1. MAHI Exo II – Elbow, forearm and wrist exoskeleton for rehabilitation, shown with participant with incomplete spinal cord injury

II. THE MAHI EXO II REHABILITATION EXOSKELETON

The MAHI Exo II (Fig. 1) is a 5 degree of freedom (DOF), electrically actuated exoskeleton device designed for elbow, forearm and wrist rehabilitation for individuals who have experienced a stroke or incomplete SCI. The robotic exoskeleton is an updated design based on work of Gupta et. al [9], and features a number of improvements aimed at overcoming issues of singularities in the wrist joint, insufficient torque output in the forearm, and passive adjustability of shoulder abduction, as discussed in [10]. The exoskeleton employs a revolute joint at the elbow for flexion/extension, a revolute joint for forearm pronation/supination, and a 3-RPS (revolute-prismatic-spherical) serial-in-parallel mechanism at the wrist. When worn by the user, the first two rotational DOF directly correspond to elbow and forearm rotations of the user. The two wrist rotations of the user (wrist flexion/extension and wrist radial/ulnar deviation) correspond to the two rotational DOF of the 3-RPS mechanism. A detailed comparison of the system capabilities with the previous design and an in-depth explanation of the design modifications can be found in [10]. A summary of these modifications are presented here for completeness.

The original design of the MAHI Exo exhibited singularities introduced by passive universal-revolute wrist ring connector joints. In the MAHI Exo II, the universal-revolute joints are replaced with Hephaist-Seiko SRJ series high precision spherical joints, resulting in a mechanical singularity free, more rigid wrist mechanism compared to MAHI Exo I. Torque output at the forearm joint was achieved while reducing cost by replacing the Applimotion 165-A-18 frameless and brushless DC motor actuator with a high torque DC motor (Maxon RE40) coupled with a cable drive transmission. Consequently, a 35% increase in torque output was achieved for less than one fourth the cost of the MAHI Exo I design. Finally, the location of the actuator and transmission at the elbow joint was modified in order to provide both left and right arm therapy, and a passive DOF was implemented which allows the therapist to set a fixed amount of shoulder abduction, resulting in improved posture for the user during training. The range of motion (ROM)

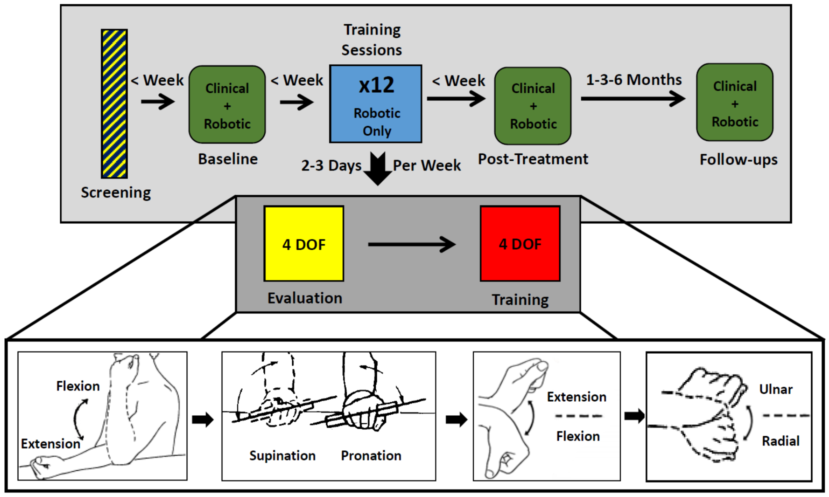

Fig. 2. The robotic training protocol includes stages for screening, baseline assessments (clinical and robotic), training, and post-treatment assessments. Training sessions include evaluation, where the subject backdrives the robot in each degree of freedom, and treatment, using a resistive mode of the robot in each degree of freedom.

and maximum achievable torque output capabilities for every joint are given in Table I.

A. Device Characterization

The experimental system characterization of the device, in terms of static friction, closed loop position bandwidth, viscous friction, and inertia was conducted to evaluate the device's potential for rehabilitation. To determine the average static friction in every joint, the actuators were programmed as a virtual spring and the response of the system to a ramp position input was measured. The inertia and viscous friction values were determined using the logarithmic decrement method [11]. The closed loop position control bandwidth of the MAHI Exo II was identified by observing the device's ability to track a sine position input with a PD controller implemented for each individual DOF. The device characteristics are reported in Table II. A more detailed explanation of the device characterization methods is given in [12].

B. Modes of Operation

The MAHI Exo II has three controlled interaction modes that are selected to be active during goal directed reaching movements to targets on a screen, described for a similar device in [13]. These modes are termed passive (for a passive subject being carried through a movement), triggered (where the subject pushes through a virtual wall with some predefined threshold force, at which time the robot carries the subject through a movement), and active-constrained (where the robot is commanded to display a force field proportional to the movement velocity at the intended joint). An additional evaluation mode, where the subject performs visually-guided target hitting tasks by back-driving the unpowered device through one of its DOFs while all other joints of the device are kept stationary via control, is used to collect position and velocity data based solely on the subject's ability.

III. Clinical Study

Clinical evaluation of the MAHI Exo II was conducted to validate the device as appropriate for larger scale clinical evaluation. We also sought to identify objective performance metrics appropriate for assessment of therapeutic gains in exoskeleton robotic rehabilitation.

A. Subjects

We recruited ten subjects (eight male, two female), all with chronic incomplete spinal cord injury (C2 through C6) with ASIA impairment levels C or D (moderate to mild disability of the upper extremities), all of whom consented to participate in the study in accordance with the human subjects protection policies of Rice University and our clinical collaborators' institutions. Eight subjects completed the study. Each subject's arms were classified as "more affected" and "less affected" (with regards to impairment caused by the SCI) based on the ASIA Impairment Scale scores.

B. Protocol

Each subject completed twelve training sessions with the MAHI Exo II using active-constrained mode. This training was preceded by a baseline clinical and robotic assessment and followed by clinical and robotic assessments post-treatment (within a week of the last training session), and at one month, three months, and six months post treatment. The protocol is illustrated in Fig. 2. The clinical assessments included ARAT, JTHFT, ASIA, Modified Ashworth Scale (MAS), grip force, and pinch force assessments (only JTHFT and ARAT will be presented in this paper). The robotic assessments involved performing twenty complete movements in evaluation mode. Data from these assessments were post-processed using a Savitzky-Golay filter with a 21-frame window to eliminate noise and then used to compute a number of metrics capturing movement quality and smoothness.

The training sessions consisted of the subject completing a prescribed number of repetitions of point-to-point movements of the specified DOF (other DOF were locked) in active-constrained mode for each joint on both arms. The graphical user interface (GUI) which guided subjects consisted of two targets which changed color to indicate the desired direction of movement and a ball which indicated subject postion (see Fig. 3) The number of repetitions and level of resistance provided by the robot were determined by the physical therapist based on subject ability and fatigue. These training sessions lasted three hours each with one and half hours spent on each arm per session. As is common in traditional therapy, time was used as the clinical consistency measure for the amount of rehabilitation received per session. The assessments and training sessions were conducted by a physical therapist who screened subjects, administered the functional assessments, and operated the robot for all of the sessions.

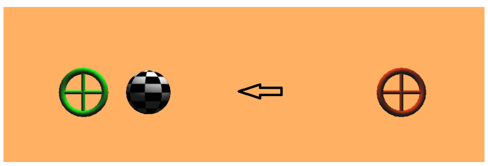

Fig. 3. The targets are located according to every subjects' active ROM capability. The assigned target is highlighted green. Once subject reaches to the target the next target is highlighted.

C. Robotic Data Assessment Measures

Velocity profile-based metrics have been shown to be effective indicators of quality of upper limb movement for point-to-point movements [6], [14], [15]. A number of different metrics have been shown to succeed in a range of domains including rehabilitation, motor learning, and surgical skills assessment. One of our objectives in this study was to examine which metrics are effective for quantifying change in the movement ability of spinal cord-injured subjects over the course of rehabilitation of the upper limb. In this study we examined speed peaks, mean arrest period ratio (MAPR), non-dimensional jerk, spectral arc length, normalized speed, and a minimum-jerk based smoothness correlation coefficient. Each of these metrics is described briefly below.

1) Number of Peaks: The Number of Peaks metric is simply the number of peaks in a velocity profile. Peaks indicate an acceleration or deceleration with more peaks per movement indicating less smooth movements. This metric has been used previously in healthy and stroke-impaired subjects [15], [16].

2) Mean Arrest Period Ratio: MAPR, originally described by Beppu et al. [17] and successfully utilized in movement analysis in stroke impaired individuals by Rohrer et al. [15], is a metric which analyzes the velocity profile of a given movement. The amount of the movement (in time) which occurs above a pre-determined percentage of the peak velocity for that movement is recorded. This time over the total movement time gives the MAPR of the movement. The threshold for MAPR for this analysis was 10 percent.

3) Non-dimensional Normalized Jerk: The normalized jerk metric is based on the average rate of change of the acceleration in a given movement. The magnitude of jerk was divided by the peak speed for each movement in order to normalize the metric as in [15]. The units output at this point for this metric would be $1/s^2$. In order to avoid the counterintuitive variations which have been shown to occur in dimensioned jerk-based movements, the dimensionless jerk metric was used [18].

$$J = \left(\frac{1}{2} \int_{T_1}^{T_2} x'''(t)^2 + y'''(t)^2 + z'''(t)^2 \mathrm{d}t \right) \cdot \frac{T^5}{PL^2} \tag{1}$$

where T is the movement duration, T_1 is the start time, T_2 is the end time, and PL is the path length.

4) Spectral Arc Length: Spectral arc length, as defined by Balasubramanian et. al [19], is a movement smoothness metric which is the negative arc length of the amplitude and frequency-normalized Fourier magnitude spectrum of the speed profile. The idea behind this metric is to examine a given movement in the frequency domain with smoother movements having more low-frequency components and less smooth movements consisting of higher frequency components. This metric is defined as

$$\eta_{sal} \triangleq -\int_{0}^{\omega_c} \sqrt{\frac{1}{\omega_c}^2 + \frac{\mathrm{d}\hat{V}(\omega)}{\mathrm{d}\omega}^2}\, \mathrm{d}\omega \tag{2}$$

where $V(\omega)$ is the Fourier magnitude of the speed profile $v(t)$ and $[0,\ \omega_c]$ is the frequency band of the movement.

5) Normalized Speed: This relatively simple metric works on the observed phenomenon that subjects with less healthy movement tend to have speed profiles with deeper valleys and more near-stops than normal movements [15]. This results in the normalized mean speed being significantly lower for impaired subjects than for unimpaired ones. Therefore, the normalized mean speed is examined as a quality of movement metric.

6) Smoothness Correlation Coefficient: Another quality of movement metric which was examined in this analysis is based on the coefficient ρ, described by Colombo et. al [20], which is based on the correlation between the velocity profile of a given movement and the corresponding minimum jerk velocity profile. In this analysis ρ was calculated as follows

$$\rho = \frac{(V_{subj} - \bar{V}_{subj})(V_{mj} - \bar{V}_{mj})}{\sqrt{(V_{subj} - \bar{V}_{subj})^2 (V_{mj} - \bar{V}_{mj})^2}} \tag{3}$$

where V_{subj} is the movement speed of the subject, V_{mj} is the minimum jerk speed profile (bar indicates mean), and V_{mj} was calculated as follows

$$V_{mj}(t) = \Delta \frac{30t^4}{T^5} - \frac{60t^3}{T^4} + \frac{30t^2}{T^3} \tag{4}$$

where Δ is the movement distance, t is time, and T is the time to complete the movement.

TABLE III

ANALYSIS OF MOVEMENT SMOOTHNESS DURING THE EVALUATION SESSIONS, MA (MORE AFFECTED) AND LA (LESS AFFECTED) LIMBS

Measure	Non-Segmented				Segmented			
	F(df) by Limb		*p*-value by Limb		*F(df)* by Limb		*p*-value by Limb	
	MA (*df* = 4)	LA (*df* = 7)	MA	LA	MA (*df* = 4)	LA (*df* = 7)	MA	LA
Speed Peaks	1.39	1.10	.3	.33	**8.64**	1.28	**.04**	.3
Normalized Speed	6.20	**9.24**	.07	**.01**	5.06	**7.45**	.09	**.03**
MAPR	1.56	2.99	.28	.13	0.09	0.10	.78	.77
Non-Dimensional Jerk	0.34	1.77	.6	.23	1.42	0.85	.3	.39
Spectral Arc Length	2.02	**4.24**	.23	**.08**	0.11	1.93	.75	.24
Smoothness Corr. Coeff.	-	-	-	-	5.29	0.11	0.08	0.75

D. Clinical Data Assessment Measures

In addition to these robotic measures, the clinical assessments mentioned previously provide valuable quantitative feedback on subject performance. Two measures in particular provide insight into the ability of subjects to complete ADL. The JTHFT [21] aims to assess a wide range of uni-manual hand functions which relate directly to ADL. The test consists of seven subtests, each scored based on how many repetitions of the subtest are completed in the given time. Each subtest ended when the subject completed the maximum number of repetitions required or reached the maximum time allowed. The score for that subtest was then generated by dividing the number of repetitions completed by the total time elapsed for the subtest. The subtests included in the JTHFT are writing a 24-letter sentence, card turning, picking up small common objects, stacking checkers, simulated feeding, moving light large objects, and moving heavy large objects. The test was modified slightly for the ability level of the subjects. The latter six subtests were used, and page turning was substituted for card turning.

The second measure examined in this study was the ARAT [22]. This test focuses on assessing upper limb function using observation. It consists of 19 tasks divided into the following four categories: grasp, pinch, grip, and gross arm movement. The tasks involve manipulating objects of different sizes and shapes such as washers, a cup of water, and a cricket ball. Each task is graded on a 0-3 point scale with 3 points given for a task completed in a normal matter, 2 points given for tasks completed with difficulty, 1 point for a partially completed task, and 0 points awarded for an uncompleted task. The grading for this study was done based on the trained observations of a physical therapist.

E. Data Analysis

One particular issue that became apparent during analysis of motion data was the inconsistency of the velocity profiles of the subjects' movement with point-to-point movements. This study aimed to have subjects perform distinct point-to-point movements in which a noticeable pause in motion occurred after each target hit and before the subject moved to the next target. However, as the result of the natural human desire to complete required tasks as quickly as possible and due to the naturally more erratic movement of the subjects given their motor impairment due to incomplete SCI, the velocity profiles generally lacked the distinct pauses expected in point-to-point movements. The repeated pseudo-point-to-point movements could not be accurately classified as continuous independent movement. So while the robotic movement quality metrics have been successfully used in both the point-to-point [14] and continuous independent movement [23] cases, the movements in this study did not fall into either category. Therefore, two approaches to the robotic analysis of the data were utilized. Each velocity profile was analyzed as a whole, with each metric representing the entire profile, and as segmented, point-to-point movements. The results of the two approaches were then compared. All metrics described above were then computed for each DOF for all sessions. Only the baseline and post-treatment sessions are compared in this paper. Some subjects could not successfully move their more affected arms on their own power in all required DOFs. Therefore, they could not successfully complete the robotic evaluation for these movements. As a result, the more affected limb data could be analyzed for only five subjects across all DOFs. In addition, the smoothness correlation coefficient requires segmentation by definition, so it was not included in the non-segmented analysis.

IV. RESULTS

The results of robotic assessment of motor impairment were analyzed using a mixed design ANOVA with more affected and less affected limb being the between subjects variable. This was done using the *a priori* hypothesis, gained from the results that the clinical data showed, that there would be a significant effect of sessions between the baseline and post-treatment evaluation data (showing improvement in quality of motion). There were significant interactions between the more affected and less affected limbs in the initial ANOVA. The *a priori* hypothesis allowed the use of simple main effects to examine the effect of sessions over baseline and post-treatment assessment for the two limbs separately. There were no significant interactions between joint and session in any of the analyses performed here. As a note, the segmented and un-segmented data were analyzed and examined separately from the beginning and, therefore, considered two different data sets in the statistical analysis. The results of this analysis are shown in Table III. From the analysis using non-segmented movement profiles, two metrics of those discussed above stood out as having increased significantly or nearly significantly across joints in one or both arms, normalized speed and spectral arc length. For the segmented analysis, speed peaks and normalized speed showed significiant differences between pre- and post-treatment assessments.

TABLE IV

FUNCTIONAL SCORES BEFORE AND AFTER ROBOTIC THERAPY

Test	Baseline	Post-treatment	$t(7)$	p-value
JTHFT (seconds)	593	503	2.69	.03
ARAT (0-57)	30.8	34.3	2.76	.03

The results of clinical assessments are shown in Table IV. Decreasing scores indicate improvement in the JTHFT while increasing scores indicate improvement in the ARAT. There were significant increases in both of these clinical measures from pre- to post-training, indicating that the robotic therapy delivered by the MAHI Exo II was clinically beneficial.

V. Discussion and Conclusions

This paper has presented the MAHI Exo II upper limb exoskeleton and results of a pilot clinical study using this device to evaluate the effectiveness of robotic rehabilitation in subjects with chronic incomplete SCI. The MAHI Exo II addresses the key issues of the previous design, namely singularities at the wrist, insufficient torque output at the forearm, inability to abduct the shoulder, and limitation to use only with the right arm. It has range of motion and static performance characteristics comparable to that of other upper limb rehabilitation robotic devices [12].

A key feature of robotic devices used for neurological rehabilitation is that the device can be used for assessment of motor impairment in addition to its primary function of delivering high intensity controlled therapy. Many studies in fundamental neural control of movement have used movement smoothness as a means of comparing movements across conditions, where movements are typically goal-directed with defined start and stop points. When applying these analysis techniques to data from participants with motor impairment due to incomplete SCI, we found that despite our intention to have subjects perform distinct point-to-point movements, instead, the subjects' movements during evaluation were quite erratic and lacking the distinct pauses expected in point-to-point movements. While the robotic metrics have been successfully applied to point-to-point movement cases, the movements in this study did not meet this criteria, and rather were more continuous in nature (almost sinusoidal though with high variability), though from time to time subjects would take rest breaks in the middle of a session to combat fatigue. Therefore, two approaches to the robotic analysis of the data were taken. Each evaluation session velocity profile was analyzed as a whole, with each metric representing the entire profile, and then again as segmented, point-to-point movements.

The aimed movements of individuals with incomplete SCI were observed to contain many accelerations and decelerations. These submovements tend to create spurious peaks when combined in the speed profile [24], adversely affecting the validity of the speed peaks metric for non-segmented data. For the segmented velocity profiles, significant change was seen in the less affected limb, but not for the more affected limb. It is likely that only a less impaired arm with greater control and movement ability can learn to execute movements in a way which eliminates excessive inflection points in the velocity profile.

One of the distinct advantages of spectral arc length is that it can be applied to entire movement profiles without penalty due to arrest periods or varying lengths durations in velocity profiles. The results in Table III show a lack of significant change in the more affected limb in terms of spectral arc length computed for non-segmented data. This finding may be related to that discussed for peaks, in that frequency of movements is relatively unaltered during the earlier stages of movement learning but refined as subjects exhibit more developed movement coordination. Spectral arc length did not provide much insight into changes in movement characteristics when segmented assessment velocity profiles were analyzed. The segmentation process cut out much of the lower velocity activity which occurred between the high velocity peaks of movement to the target. However, many of the complex submovements in these velocity profiles occurred at lower velocities. Therefore, the segmented velocity profiles tended to be similar with regard to their Fourier magnitude spectrum over the course of training even though the lower velocity movements improved over the course of training.

MAPR has the weakness of being insensitive to fluctuations and complexity changes which occur at speeds away from the defined threshold value [17]. As discussed, much of the change in the velocity profile across training appears to have occurred in the lower velocity submovements. While maximum velocity and complexity may have changed, the proportion of movements which occurred at the higher velocities did not change. Therefore, MAPR did not indicate significant change in either the segmented or the non-segmented analysis

The main issue with the non-dimensional jerk metric for the non-segmented data occurred when a subject ceased moving for a period of time. In this situation the T^5 term increases while the PL^2 term does not, which results in a drastic increase of the value in the metric. This situation occurred often enough to create a very large amount of outliers and effectively render this metric of little value. The lack of significant change in this metric for the segmented data likely has to do with the segmentation method and the fact that the movements in these velocity profiles were not truly point-to-point.

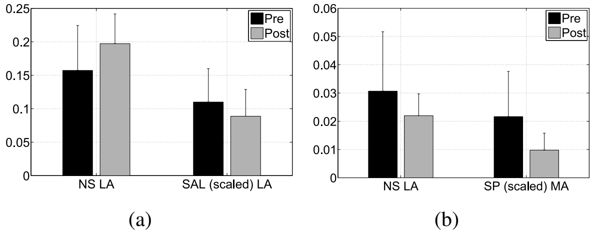

Fig. 4. Box plots of metrics which showed statistically significant change from pre-training assessment to post-training assessment. NS, SAL, and SP stand for norm speed, spectral arc length, and speed peaks respectively. LA and MA stand for less affected and more affected respectively. Spectral arc length and speed peaks are both scaled to fit. (a) non-segmented data (b) segmented data

One metric which showed significant change in both analysis methods was normalized speed. As seen in Fig. 4, the normalized speed in the less affected arm increased in the non-segmented data and decreased in the segmented data. In the non-segmented data, the local minima, or valleys, which held the norm speed down must have decreased in severity over sessions while the maximum speed became slightly lower (a possible indication or improving movement control). In the segmented data, these valleys would not be accounted for as much in the segmented data. Therefore, the decrease in maximum speed would account for the decrease in normalized speed. Further analysis would be required to determine in which case the normalized speed would be a more effective metric.

The improvements seen in the ARAT and JTHFT indicate improvements in ability and function for the subjects who completed the prescribed protocol. This in itself shows the utility of the MAHI Exo II. However, in the future it would be beneficial to have robotic metrics which can accurately represent improvement in ability and function by examining movement quality. Future work with this device will focus on determining which robotic measures will best fill this role.

It is imperative to ensure that evaluation-type movements done for robotic assessment fall into well-defined types of movement. Improvements to the control modes and graphical user interface have the potential to constrain movements to be truly continuous or point-to-point reaching type. Specific input and instruction from the therapist is also required to keep the subject from taking the easiest route through the prescribed evaluations.

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