

Upper limb bilateral symmetric training with robotic assistance and clinical outcomes for stroke

Robotic assistance and clinical outcomes

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A pilot study

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Abstract

Purpose – The purpose of this paper is to evaluate the physiotherapeutic benefits of bilateral symmetric training (BST) for stroke survivors affected by hemiparesis.

Design/methodology/approach – Other studies have investigated symmetric physiotherapy. A key difficulty in previous work is in maintaining mirror-imaged trajectories between the affected and less-affected limbs. This obstacle was overcome in this work by using a two-armed robotic exoskeleton to enforce symmetry. In total, 15 subjects, > 6 months post stroke were, randomly assigned to bilateral symmetric robotic training, unilateral robotic training, and standard physical therapy.

Findings – After 12 training sessions (90 minutes/session), the bilateral training group had the greatest intensity of movement training. They also had the greatest improvement in range of motion at the shoulder. The unilateral training group showed the greatest reduction in spasticity.

Research limitations/implications – The rationale for symmetric physiotherapy is that it might promote connections from the undamaged brain hemisphere. The robot generated copious amounts of detailed kinematic data. Even though these data provided insights into the human to machine interface using different training modalities, it proved difficult to draw neurological conclusions. It is recommended that future research along these lines should include measures of neurophysiological change and/or changes in neurological activity.

Practical implications – This research suggests that the advantage of bilateral symmetric movement over other modalities is slight, and that robotic training has comparable results with standard care. If BST is used, care is potentially needed to avoid exacerbation of spasticity. Finally, this research includes a novel quantitative approach for evaluating robotic training.



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Originality/value – This study is of value to therapeutic researchers interested in new physiotherapy techniques, roboticists interested in developing rehabilitation devices, or for rehabilitation game designers interested in using virtual reality.

Keywords Robotics, Virtual reality, Data mining, Real-time systems, Stroke survivors, Physical therapy, Stroke, Bilateral, Symmetric

Paper type Research paper

1. Introduction

In the USA, stroke is a leading cause of disability (Muntner *et al.*, 2002). The majority of survivors experience hemiparesis and require rehabilitation (Kaste *et al.*, 1998). A variety of therapeutic approaches based on neural adaptive potential have been proposed over the years. Among these are task-specific practice forcing unilateral training with the hemiparetic side and bilateral training performing tasks requiring both hands (Cauraugh *et al.*, 2010; Stewart *et al.*, 2006). Task-specific activities are advocated, in part, for their practical importance in recovering independence in activities of daily living (ADL). For the lower limbs, bilateral coordination is essential to enable walking and balance. For the upper limbs, ADL tasks requiring bilateral coordination would include tying shoes, driving a car, picking up a heavy or large object, or stabilizing a glass to pour a drink. The neurological basis for unilateral training is to increase neurogenesis and recovery around the site of the lesion. On the other hand, the rationale for bilateral therapy is that it might elicit a more distributed pattern of motor activity in both hemispheres of the brain. These include the sensorimotor cortex, cingulate motor cortex, lateral pre-motor cortex, superior parietal cortex, and cerebellum (Cauraugh *et al.*, 2010).

Most commonly, a cerebral vascular accident (CVA) results in damage (infarct) to a cerebral hemisphere. When motor function is affected, the contralateral limb is primarily impaired. However, it is now known that there may be some deficits on the ipsilateral side as well. Based on principles of neuroplasticity, it is thought that the distributed nature of bilateral training, as opposed to unilateral training, might promote recovery through activation of multiple brain areas. However, some argue that the multiplicity of activation sites may emphasize compensatory rather than direct recovery of function around the site of the lesion (Cattaert *et al.*, 1999; Cauraugh and Summers, 2005). Restricting the use of the unaffected hemisphere is an important component of constraint-induced therapy where the less-affected upper limb is immobilized with a sling or a glove (Taub *et al.*, 1999). Thus, the question is whether bilateral training interferes with the recovery of the affected limb by using the non-lesioned hemisphere (Mudie and Matyas, 2000). Indeed, the benefits of bilateral therapy are still in dispute and the research results are mixed (Cauraugh *et al.*, 2010; Stewart *et al.*, 2006).

In recent decades, rehabilitation robotics has garnered increasing attention. There are a variety of designs for upper limb rehabilitation robots. Some designs target the wrist (Krebs *et al.*, 2007; Hesse *et al.*, 2003; Frick and Alberts, 2006) while others target the shoulder and elbow. Some systems interact with both arms simultaneously, while others interact with one arm at a time (Krebs *et al.*, 1999; Montagner *et al.*, 2007; Rosati *et al.*, 2007; Amirabdollahian *et al.*, 2007; Toth *et al.*, 2005). For this work, we consider a robot that interacts with both arms, bilaterally, and that targets the shoulder, elbow, and wrist. One variant of bilateral training makes use of symmetric movement. Based on experiments relating to bilateral symmetric manual coordination using transcranial magnetic stimulation and kinematic modeling, symmetric movement might reduce inhibitions between the left and right hemispheres (Kagerer *et al.*, 2003; Cattaert *et al.*, 1999).

In other words, bilateral symmetric movements have been found to increase cross-talk in the corpus callosum. In that vein, multiple studies have demonstrated the effectiveness of mirror therapy. Using mirror therapy, stroke survivors were able to improve function based on the optical illusions of their paretic arm moving normally (Yavazer *et al.*, 2008; Sutbeyaz *et al.*, 2007). Based on such research, it has been proposed that symmetric training might exploit such coupling thereby allowing for increased use of undamaged ipsilateral projections (Cauraugh and Summers, 2005). In this way, symmetric training might improve the recovery process after a CVA.

Others have studied the effects of bilateral symmetric robotic training. One question naturally arises as to how symmetry is achieved. One approach is to ask the subjects to execute tasks symmetrically. Such tasks might include picking up blocks, or rolling cylinders with both hands. It is therefore the responsibility of the subject to try to maintain symmetry between each arm (Desrosiers *et al.*, 2005). Under such a protocol, the paretic side will likely accomplish tasks differently from the unaffected side. Thus, visual and afferent feedback is essentially asymmetrical. This format of intervention would, perhaps be better described as volitional bilateral symmetric movement training.

Another approach to studying bilateral, symmetric movement training involves rigidly enforcing symmetry. One method to enforce symmetry is through the use of mechanical coupling between the arms (Chang *et al.*, 2007). For example, in one experiment a “robot” with a single degree of freedom (DOF) was used to enforce symmetry. This robot was similar to a mechanical bench press in that the hand grips were unable to move independently. Therefore, the affected arm was forced to move symmetrically. Others have used more sophisticated robots that involve a greater number of DOF in the arm for isokinetic training (Lum *et al.*, 2002). In the rigidly enforced symmetrical training, the paretic limb will always be moved through space, even if it is entirely flaccid. A possible drawback to isokinetic movement training is that the paretic arm motions require little to no volitional movement. Passive movement training is generally not associated with improved voluntary movement (Timmermans *et al.*, 2009). In addition, for research involving bilateral robotic training, often the training was not exclusively bilateral symmetric training (BST), but rather a mix of unilateral and bilateral training.

This research used a robotic exoskeleton to provide BST as well as unilateral training. The kinematics of both training modalities was then assessed against clinical outcomes. The overall goal is to characterize BST in terms of training intensity and to compare it against unilateral asymmetric training (UAT). The kinematic differences in training groups are then evaluated against clinical outcomes. There were two robotic intervention groups: two-armed, mirror-imaged (BST) and one-armed (UAT). Each robotic movement training group participated exclusively in bilateral symmetric or unilateral movement training. Unlike previous work involving isokinetic training, the robot in this study provided partial assistance for all robotic training (Secoli *et al.*, 2011; Lum *et al.*, 2002). Partial assistance is regarded as preferable because it encourages self-initiated movement (Marchal-Crespo and Reinkensmeyer, 2009). The control, or comparison group, performed conventional task-specific training with a physical therapist (usual care) (Lum *et al.*, 2006).

2. Methods

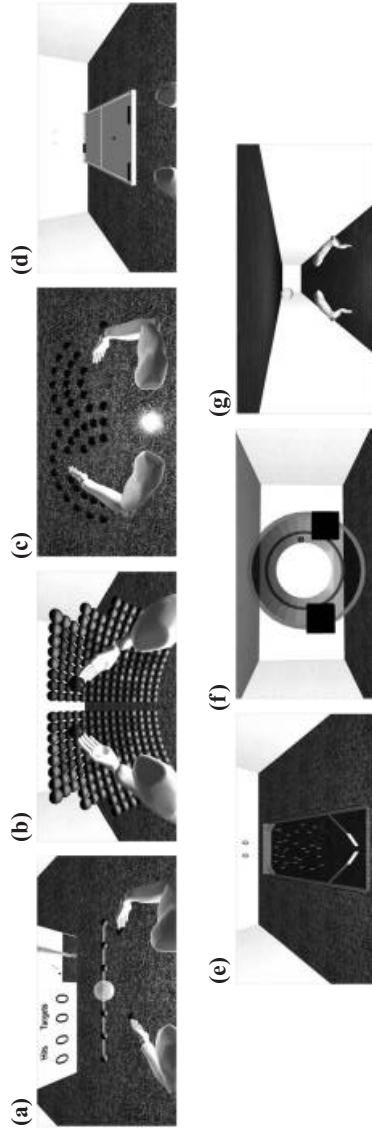
2.1 Apparatus

The system used for this research consisted of a rehabilitation robot, a control computer, and a game computer. The robot was a two-armed, 14-DOF exoskeleton termed the EXO-UL7 (Perry and Rosen, 2007). Force data were collected from six

different ATI Mini-40 transducers located at the human to machine interfaces of the EXO-UL7. One transducer was located midway on the upper arms, another below the wrists, and a third above the hand grips. Position data were collected from 40,000 count optical encoders housed within each of the 14 motors of the EXO-UL7. The control computer used proportional-integral-differential control to provide gravity compensation (Miller, 2006), as well as bilateral symmetric assistance or unilateral assistance, as needed. Gravity compensation was only used to compensate for the robot's weight and not for the weight of the subject's arm. Even though integral control attempts to drive the motors to reduce position errors to zero, persistent position errors were often present to various extents because the motor drivers were current limited. By "current limiting" the motors, an upper bound was essentially imposed on the amount of torque the robotic electric motors could produce. The robot could only exert forces on the arm up to a certain threshold. Thus, in all cases where assistance was provided the robot only provided partial assistance, helping subjects by providing force in the desired direction (Secoli *et al.*, 2011; Lum *et al.*, 2002). The amount of assistance provided is revisited in "Results."

The games were created using Microsoft Robotic Developer Studio, 2008 (Microsoft Inc., Redmond, WA, USA). The game computer was connected to a 50-inch flat screen monitor. In addition to generating real-time virtual reality (Krakauer, 2006) game images, the game computer also collected position and force data at 100 Hz. The virtual games were controlled using the joint angles of the robot. The games are depicted in Figure 1. Full-arm movements in flower, paint, reach, and handball, were generated using a forward kinematic model of the avatar arms. The Pinball game was unique in that the paddles were simply actuated by wrist flexion and extension. The Pong and Circle games utilized a paddle that was constrained to a linear path. This path was a straight line for Pong and a curved line for Circle. For Pong and Circle, the game computer positioned the virtual paddle along these lines such that the paddle was closest to the virtual location of the hand. Thus, the subjects were able to move the paddles even though the avatar hands were imprecisely located along the paddle trajectories.

The BMT group played each game using both arms and the UAT group played each game using only the paretic arm. For BMT, the subject's less-affected arm was the master, and the paretic arm was the slave. As subjects moved their less-affected arm the robot moved the paretic arm in a mirror-image fashion. This was accomplished in software by using the joint angles of the less-affected arm (master) as a command signal for the joint angles of the more-affected arm (slave). Aside from gravity compensation, for UAT, the robot only provided partial assistance in the Flower game (see Figure 1(a)). For the Flower game, the robot helped to guide subject's arms to static targets. UAT partial assistance was only provided for the Flower game due to control constraints that arose for the remaining "dynamic" games. In this context, dynamic games involve moving targets, such as a bouncing ball. Such games involve timing, and with the exception of Pinball, an infinite number of possible hand trajectories to reach a given target. When attempts were made to provide assistance for such games during the development of the system, the assumed timing, speeds, and directions of robotic assistance did not necessarily match what the game players intended to do. Thus, it often felt as if players had to fight the robot during game play (Simkins *et al.*, 2012). The Flower game utilized fixed targets. Therefore, the assistance was easily implemented for UAT. The robot simply attracted the hand toward fixed targets in space. BMT was also easy to implement because the less-affected arm dictated assistance commands and no prediction was required.



Notes: For visibility, only the avatar arms are presented to subjects for most games. Avatar arms are not visible in the Pinball and Circle games. (a) Flower game; (b) paint game; (c) pong game; (d) pinball game; (e) circle game; and (g) handball game

Figure 1.
Screen shots from
the various games

2.2 Subjects

This research was approved by the University of California, San Francisco, Committee on Human Research. Included were 15 subjects > 6 months post stroke. All subjects provided written consent prior to participation in this study. Demographic information is provided in Table I. The subjects were stratified by Fugl-Meyer score and then randomly assigned to the BMT, UAT, or usual care with a physical therapist. With an upper limb Fugl-Meyer score between 16 and 39, each subject had the necessary control of their paretic arm to be able to play the games while still having the potential for improvement.

Interventions consisted of 12, 90-minute sessions of robotic BMT, robotic UAT, and standard care. An elastic restraint around the torso and thighs helped subjects maintain a neutral sitting position during robotic training. The experimental setup for robotic training is depicted in Figure 2. For robotic training, the virtual games depicted in Figure 1 were played for 10-15 minutes each for both BMT and UAT. Over the course of the study each subject played every game multiple times. Therefore, the rehabilitative efficacy of any given game is confounded with the other games (Kato, 2012). Subjects receiving standard care participated in 90-minute long sessions with a licensed physical therapist. This therapy utilized learning-based, task-oriented, repetitive training that is based on principles of neuroplasticity (Cramer and Riley, 2008; Adkins *et al.*, 2006; Kleim and Jones, 2008). For each session subjects were assessed for range of motion (ROM) on their most affected side using the EXO-UL7. Subjects were asked to perform isolated rotate along each joint axes. Subjects rotated their joint to the minimum achievable angle in extension, and the maximum angle in flexion. The differences between these two angles were recorded.

2.3 Improvement metrics

This work narrows in on a fraction of clinical measures that were gathered from this study. The measures considered presently include: spasticity using the Ashworth scale (Bohannon and Smith, 1987), dexterity with the Box and Block test (Mathiowetz *et al.*, 1985), hand strength as measured with a Jamar[®] hand dynamometer (Lafayette Instrument Company, Lafayette, IN), and shoulder ROM) as measured using a plastic goniometer. The reason for focussing on these measures is explained in the Statistics portion of "Data analysis." The total list of clinical tests that were performed also includes the Fugl-Meyer Assessment (Duncan *et al.*, 1983), ROM along all joint axes of the shoulder, elbow and wrist, lateral pinch, three-point chuck, manual muscle testing of the wrist, elbow and shoulder (Kendall *et al.*, 1993), wolf motor function (Wolf *et al.*, 2001), finger tapper (Spreen, 1998), digital reaction time (Bohannon, 1995), the Saint Louis University Mental Exam (Tariq *et al.*, 2006), the Beck Depression Inventory (Beck *et al.*, 1961), and pain scales. Clinical results for this study are discussed in Byl *et al.* (2013). However, kinematic results collected from the robot, and their relation to specific clinical outcomes was not considered in that work.

2.4 Data analysis

Over the past decades a large number of metrics have been proposed to assess human movement using robots and/or motion capture (Secoli *et al.*, 2011). There are two difficulties with such approaches. First, it is often unclear if a change in a given metric was caused by legitimate rehabilitation or if it is related to familiarity with the system. For example, a subject might improve at playing a given game even though there is no actual therapeutic improvement. Second, real-time, multi-joint force, and velocity data

Type	Sex	Age	Affected side	Spasticity – Ashworth		Box and block	Grip strength	Shoulder ROM (degrees)		Initial Fugl-Meyer	
				Finger flex.	Elbow ext.			Elbow flex	Abd.		In. rot.
Bilateral (BMT)	M	72	Right	4	0	19	18.3	60	50	0	28
	M	58	Right	5	1	23	34.7	30	55	63	29
	M	66	Right	5	3	0	20	85	40	0	16
Unilateral (UAT)	M	62	Left	1	1	10	16	90	50	10	23
	M	68	Right	2	2	0	16	100	25	40	26
	F	61	Right	2	2	7	12.5	80	70	50	19
	M	76	Right	3	4	17	46.7	80	15	45	36
	M	44	Right	5	4	0	38	80	30	35	18
	M	24	Left	3	3	1	42.7	110	45	70	19
Standard care	M	66	Left	1	3	6	35.7	85	65	10	27
	M	71	Left	2	1	10	35.3	70	65	70	31
	M	68	Right	4	3	7	33.3	80	70	85	33
	M	34	Right	2	1	0	7	80	65	70	20
	F	62	Left	5	4	0	55.3	90	70	80	19
	M	62	Right	3	2	0	12.7	40	15	10	20

Notes: Abd., abduction; In. Rot., inner rotation; Ext. Rot., external rotation

Table I.
Subject
demographics



Figure 2.
A subject with right-
side hemiparesis
performing BSRMT

are generally not available in clinical settings, nor are they standardized. Therefore, measures that are gathered from a given robotic system are difficult to replicate without access to such systems. It is also unlikely that they directly translate to standard clinical measures. For these reasons, this research focussed on clinical measures of performance that were collected before and after the intervention. Kinematic data collected from the robot are used to contrast training modalities, but kinematic data are not used to measure or assess improvement. For a kinematic analysis that attempts to measure improvement by comparing hemiparetic stroke survivors to neurologically intact subjects (see Kim *et al.*, 2013).

“Data analysis” references joints by number. The directions of positive joint rotation are depicted in Figure 3. In words, the axes are defined as follows. Joint 1, is a combination of shoulder flexion and abduction; Joint 2, is a combination of shoulder flexion and adduction; Joint 3, shoulder inner rotation; Joint 4, elbow flexion; Joint 5, elbow/wrist supination; Joint 6, wrist flexion; and Joint 7, wrist ulnar deviation.

In an effort to tie clinical outcomes to training, a metric is needed to quantify overall movement training. A long-standing tenet in the rehabilitation community is that repetition of movement is required for recovery. Accordingly, if the overall quantity of movements were higher, this would suggest that the subject engages in more repetitions. Furthermore, slow movements through small distances in the paretic arm would suggest that the training modality elicits a comparatively weaker, less-effective repetition as compared to larger, more vigorous repetitions. Thus, this training evaluation focusses on the overall intensity of movement. Ordinarily, an evaluation of training intensity is a subjective measure performed by a therapist, trainer, or coach. The proposed intensity measure is more objective in that it is calculated from kinematic data. However, it is not presented as an absolute measure either. For any given intensity number that is calculated, no claims are made here as to whether or not the number is “better” or “worst.” Instead, the intensity measures are used in this work as a

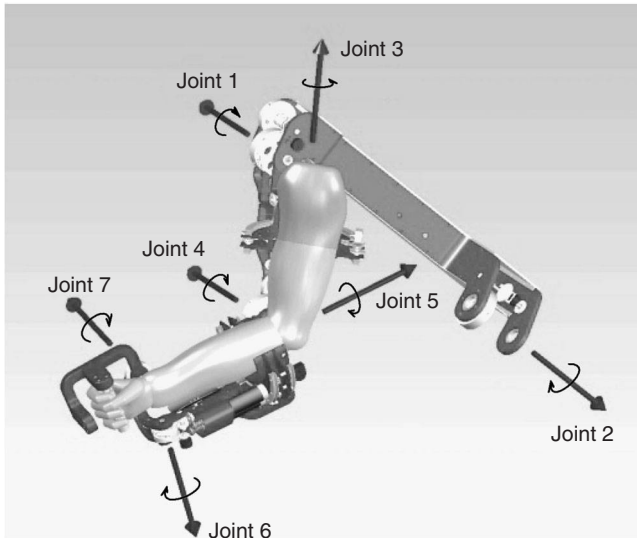


Figure 3.
A breakout of the
linkages for the right
arm of the EXO-UL7

means of comparison between UAT and BST. Even though the scope of this work is to use intensity as a means of comparison between UAT and BST, the methodology could conceivably be used to compare therapeutic games, or even therapeutic systems. Intensity calculations include data that spans from the start of game play to the end of that game. Arm movements associated with stretching and warming up, entering and exiting the robot, and breaks or stops, are not included. Because the training could cause subjects to exercise some muscle groups at the expense of others, the proportion of movement for each joint is also considered.

To quantify overall movement training for a given game during a given trial, seven numbers are calculated, one for each joint. Each of the seven numbers relate to the proportional contribution of movement for a given joint. An eighth number is calculated to capture the overall intensity of movement. With respect to the proportions of movement for each of the seven joints, a row vector is defined as follows:

$$|p_1 \ p_2 \ p_3 \ p_4 \ p_5 \ p_6 \ p_7| \quad (1)$$

where p_1 is the proportion of rotation for Joint 1, p_2 is the proportion of rotation of Joint 2, and so on. Accordingly:

$$p_1 + p_2 + p_3 + p_4 + p_5 + p_6 + p_7 = 1 \quad (2)$$

Thus, the sum of the proportions account for 100 percent of the total joint rotation for the seven DOF of the arm. The eighth number being calculated is the “intensity” of the training and is given by I . Thus, the root mean square (RMS) for a measure of joint j is given by $p_j \times I$.

Equations (1) and (2) require some measure of movement training intensity. One approach is to calculate total angular position, velocity, and acceleration for a given joint. As a start, consider angular position. A change in angular position is given by $\Delta\Theta$ where Θ is a joint angle measured in radians. Summing $\Delta\Theta$ for successive samples in

the data set is infeasible because rotations in one direction will cancel with rotations in the other direction. Therefore, a more suitable calculation for angular position of the j th joint is to take the RMS as follows:

$$RMS_{\Theta_j} = \sqrt{\frac{1}{n} \sum_{i=1}^n \Delta\Theta_{i,j}^2} \quad (3)$$

where n is the number of joint measurements, and i is the i th measurement. Angular velocity, ω is given by $\Delta\Theta/\Delta t$. Therefore, the RMS for ω is given by:

$$RMS_{\omega_j} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{\Delta\Theta_{i,j}}{T_s} \right)^2} \quad (4)$$

where T_s is the sample time. In this case, the sampling rate was 100 Hz and $T_s = 0.01$ s. Because T_s is a constant, (3) is essentially the same calculation (4) except that it is scaled by the constant value $1/T_s$. Therefore, calculating the RMS of both angular position and angular velocity is of little value and the discussion that follows considers only angular velocity and acceleration.

In an effort to minimize the affects of noise and finite sampling times, five-point numerical differentiation was used to calculate the RMS for angular velocity and acceleration. Thus, the RMS calculation that is used for velocity is:

$$RMS_{\omega_j} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{-\Theta_{i+2,j} + 8\Theta_{i+1,j} - 8\Theta_{i-1,j} + \Theta_{i-2,j}}{12T_s} \right)^2} \quad (5)$$

and for angular acceleration:

$$RMS_{\alpha_j} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{-\Theta_{i+2,j} + 16\Theta_{i+1,j} - 30\Theta_{i,j} + 16\Theta_{i-1,j} - \Theta_{i-2,j}}{12T_s} \right)^2} \quad (6)$$

With the RMS calculations for angular acceleration and velocity in hand, calculating the proportional contributions of each joint according to (1) is obtained by the following expression:

$$\left(\sum_{j=1}^7 RMS_j \right)^{-1} |RMS_1 \quad RMS_2 \quad RMS_3 \quad RMS_4 \quad RMS_5 \quad RMS_6 \quad RMS_7| \quad (7)$$

The proportions given in (7) are presented as percentages throughout this paper. The total intensity I is calculated for each game of each trial for both angular acceleration and angular velocity by summing the RMS values across the seven joints. The intensity calculation is given as follows:

$$I = \sum_{j=1}^7 RMS_j \quad (8)$$

Forces were recorded along orthonormal axes and are reported here as the magnitude of their vector sum. Average forces, μ , were calculated using the following expression:

$$\mu = \frac{\sum \sqrt{x_i^2 + y_i^2 + z_i^2}}{m} \quad (9)$$

For (9), m is the number of samples. Variables x , y , and z are the projections of force onto the coordinate frame defined by the force sensor for the i th timestamp in the data set.

Data processing was accomplished using custom MatlabTM scripts (The Mathworks Inc., Natick, MA, USA).

2.5 Statistical

Clinical data were analyzed using standard hypothesis testing. Specifically, for each test type the corresponding subject groups were tested for a change in performance as measured before and after the intervention. This includes paired t -tests for parametric measures and Wilcoxon signed-rank tests for non-parametric data. These hypothesis tests assume normality for parametric data and symmetry for non-parametric data. Parametric data were assessed for normality using a visual examination of probability plots that included normality bounds. All parametric statistical tests that are reported here utilize data that passed this normality test. Similarly, non-parametric data were evaluated for symmetry by calculating the differences between post-study and pre-study evaluations, and then by generating probability plots of the differences. Again, the differences for non-parametric data passed this normality test. Thus, the non-parametric data are assumed symmetric. For both types of tests, p -values were reported. Statistical calculations were performed using Minitab Statistical Software (Minitab Inc., State College, PA, USA). A confidence limit of 95 percent ($p < 0.05$) was used to test significance. However, given the comparatively small population of subjects in each training group ($n = 5$), and the comparatively large number of hypothesis tests being performed, these tests are being reported here as possible trends only. Additionally, values of $p < 0.15$ are also reported for information purposes.

As was mentioned previously, 17 different clinical evaluations were performed. In one sense, evaluating so many clinical metrics is good because the evaluation is more comprehensive. In another sense, evaluating so many metrics increases the likelihood of a type I error. Robotic therapy has been shown to provide positive trends in Fugl-Meyer scores. However, in many cases they do not reach the level of statistical significance (Kwakkel *et al.*, 2007). Achieving such a high level of confidence for any given measure is a high bar. Notwithstanding, none of the two-sample hypothesis tests achieved that level of significance for clinical measures. Generally speaking, these considerations result in the paradoxical situation in which a study must include as few measures as possible in order to achieve statistical significance. Thus, the pairwise statistical tests being performed in this work are only presented in order to demonstrate the greatest trends (see Table II). This approach was deemed preferable to reporting the largest average differences in pre-intervention and post-intervention measures. This is because hypothesis tests include the effects of variation in addition to average differences. By that standard, Table II includes clinical measures that show the largest trend. In the strictest sense, none of the clinical measures, by themselves are statistically significant. This is a pilot study and it is left to the discretion of the reader how to interpret these levels. The value of presenting these findings is that they

Category	Test	Units	BMT median difference	BMT 1st quartile	BMT Wilcoxon <i>p</i> -value*	UAT median difference	UAT 1st quartile	UAT Wilcoxon <i>p</i> -value*	Standard care median difference	Standard care 1st quartile	Standard care Wilcoxon <i>p</i> -value*
Non-parametric	Spasticity	Ashworth finger flexor	Ordinal	-1	0.07	-2	-3	0.07	-1	-2	0.11
	Spasticity	Ashworth elbow	Ordinal	0	0.47	-1	-2	0.11	0	-1	0.18
	Spasticity	Ashworth elbow extensors	Ordinal	-1	0.36	-2	-3	0.11	0	-1	0.79
Parametric	Dexterity	Box and block	BMT average percent change	BMT % change SD	BMT paired-T <i>p</i> -value	UAT average percent change	UAT % CHANGE SD	UAT paired-T <i>p</i> -value	Standard care average % change	Standard care % change SD	Standard care Paired-T <i>p</i> -value
	Strength	Grip	9	29	0.70	103	129	0.10	10	22	0.37
	ROM	Shoulder abduction	32	56	0.45	-16	8	0.03	-11	57	0.45
	ROM	Shoulder internal rotation	42	53	0.05	18	17	0.08	48	42	0.03
	ROM	Shoulder external rotation	-2	56	0.93	-14	14	0.09	29	82	0.81
	ROM	Shoulder external rotation	24	34	0.07	56	33	0.75	34	109	0.67

Notes: If Bonferroni correction factors are neglected, dark shaded italic type would correspond to $\alpha \leq 0.05$, light shaded italic type would correspond to $\alpha \leq 0.15$. The Ashworth test was scored on a 0-5 scale. *These *p*-values do not indicate a statistically significant difference. Instead, they indicate the strongest trends observed

provide guidance so that future research can narrow in on specific outcomes without diminishing their statistical power by measuring unpromising outcomes. Statistical hypothesis tests that relate to training intensity differences in UAT and BMT compare kinematic differences, not clinical measures. Therefore, statistically significant claims are made in association with (1)-(9).

3. Results

3.1 Clinical measures

Table II summarizes all clinical measures of performance. For each group the average percent change is calculated for parametric data. For non-parametric data the median change is calculated. Also, a p -value for the corresponding hypothesis test (paired- t or Wilcoxon) is given next to each average percent (parametric), or median change (non-parametric). Italic type indicates possible differences. The strongest changes, $\alpha \leq 0.05$, are distinguished with a dark shade of cell gray. For $0.05 < \alpha \leq 0.15$ the cells are distinguished with a lighter shade of gray.

As is evident in Table II, there was a possible reduction in finger flexion spasticity for all subjects. For UAT there was a possible reduction in elbow flexion/extension spasticity for UAT as well as a possible improvement on the Box and Block test. However, there was a possible reduction in grip strength for UAT. There were possible differences for ROM (Andrews and Bohannon, 1989) in the shoulder for all three groups. There was a relatively large improvement in shoulder abduction for the BMT and the standard care groups. The subjects in the BMT group also had a possible improvement in shoulder external rotation ROM. The UAT group had the least improvement in shoulder ROM. In addition, the BMT group had a possible reduction in internal rotation ROM at the shoulder.

3.2 Applied forces

For perspective on the amount of assistance provided, bilateral partial assistance forces for one session of the Flower game were calculated according to (9). The Flower game provides a good representative sample for forces because a subject must perform reaching trajectories in all directions. On average, the robot provided a modest 16 N of partial assistance during a 15-minute session of game play as measured by force transducers at the humerus, forearm, and hand.

3.3 Movement training measures

At times subjects would pause their movement training. The causes for such halting could result from a variety of reasons. Examples include: stops for technical corrections for the robot or game, readjustments of straps or restraints, dialog with the subjects, respites, and bathroom breaks. As a specific example, a training interval of approximately 300 seconds is depicted in Figure 4. Notice that there are two apparent pauses wherein most of the joints stop moving (flat lines). Pauses such as this will deflate the measures given by (5) and (6). Perhaps the most accurate measure of training intensity (8) and percent contributions (7) would consider only data with the pauses removed. However, such segregation of data are open to interpretation and is fraught with uncertainty. For this reason, the following analysis will consider data sets only for the top 50th percentile of training as measured by intensity. Cases where training is halted will result in lower intensities. Therefore, by excluding the lower half of the data it is more assured that data analysis only includes training that was continuous and without interruption.

Figure 4.
Joint pauses during
bilateral training

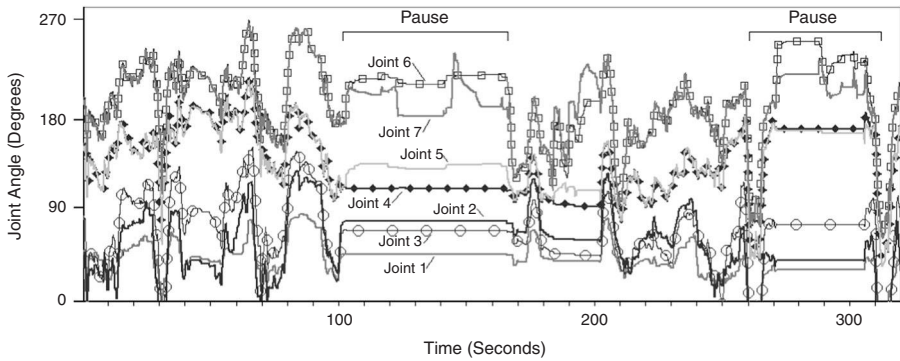
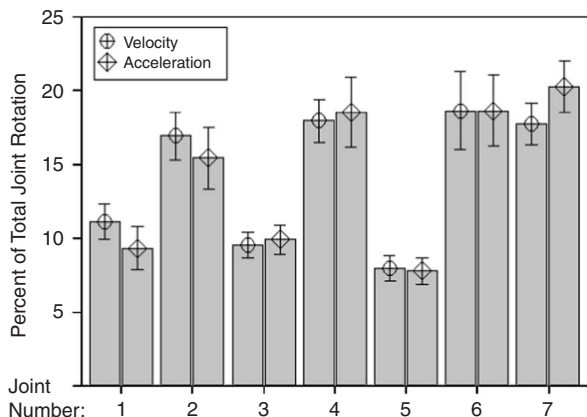


Figure 5 depicts UAT percentage contributions by joint for velocity (5) and acceleration (6). Each element in (7) is summarized statistically as a CI for velocity and acceleration. Notice that angular velocity and acceleration track fairly closely for each joint. In general, based on the percent contributions of each joint, and the training intensities, velocity, and acceleration tended to co-vary. Put another way, comparing BMT and UAT using velocity was roughly equivalent to using acceleration. Therefore, considering the differences between BMT and UAT in terms of velocity and acceleration are of little value. Thus, with the proviso that acceleration would have been an equally valid measure, the remainder of this paper will consider only velocity RMS values.

Depicted in Figure 6 is a comparison of the affected arm to the control arm for BMT. Figure 6 also provides the first full graphical embodiment of (1) and (8). For the sake of clarity, we use Figure 6 to calculate the average angular speed of the elbow, Joint 4, for the control arm. As is evident from the graph, the average proportion of movement for Joint 4 is 12.7 percent, or 0.127. The average intensity is 3.02. To calculate the average RMS velocity, simply multiply the average intensity by the average proportion, or $0.127 \times 3.02 = 0.34$ radians/second, or 22 degrees/second. Therefore, on average, the less-affected elbow moved with an RMS speed of 22 degrees/second. This calculation works equivalently for any given joint, any individual measure, or for acceleration. Perhaps not surprisingly, the control arm had similar joint contribution percentages as the affected hemiparetic arm. The affected arm was possibly lower in intensity than the

Figure 5.
Joint percentages for
velocity and
acceleration for all
unilateral subjects



control arm, $p = 0.017$ (see “All joints” in Figure 6). In other words, even with robotic partial assistance on the affected side, the less-affected arm moved more rapidly than the more-affected arm.

3.4 Bilateral symmetric vs unilateral training

Because the improvement of the affected side is most important, the following comparison between BMT and UAT considers only the paretic arms. This comparison is summarized in Figure 7. The most important difference was in terms of intensity. The right most set of CI's in Figure 7 depicts the overall intensity of bilateral vs unilateral training as calculated by (8). A two-sample t -test indicated that there was a statistically significant difference in intensity between the two training groups (p -value < 0.001) with BMT having a mean intensity that was 25 percent higher than UAT. Additionally, Figure 7 shows a significantly lower proportion of movement in the elbow for BMT than for UAT (p -value < 0.001) with BMT having a mean proportion that was 33 percent lower than UAT. The cause for this difference is revisited in “Results.” Thus, the EXO-UL7 seems to have had difficulty flexing and extending the elbow as it attempted to maintain symmetry between the paretic arm and the faster moving unaffected arm.

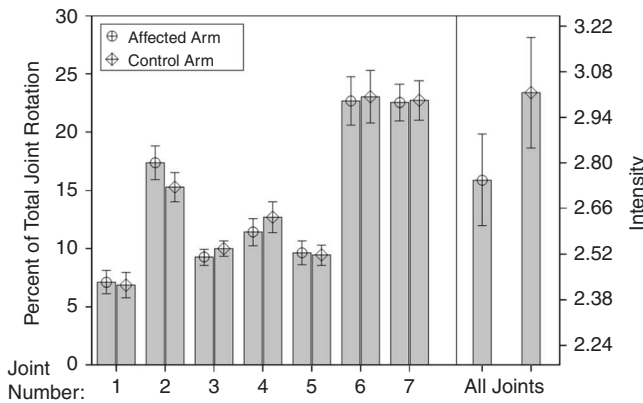


Figure 6. Bilateral percent contributions by joint of the control arm (unimpaired arm) vs the slave arm (affected) arm

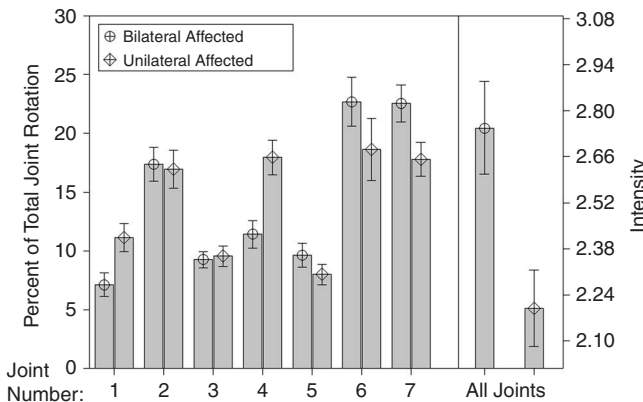


Figure 7. BSRMT versus URMT

One of the drawbacks to Figures 5-7 is that they do not convey how much ROM subjects were able to achieve while using the EXO-UL7. Table III summarizes the ROM for all subjects for each joint while they were wearing the robot.

4. Discussion

The UAT group demonstrated a greater decrease in tone and the BMT group demonstrated greater gains in ROM. Using the approach described in "Data analysis," position, velocity, and acceleration were approximately equivalent measures of intensity. This approach also allowed for more detailed comparative analysis of training. With respect to differences between the less-affected control arm and the affected arm for BMT, the paretic arm did not always move as far, or as fast as the less-affected arm. This difference is explainable by the fact that the robot provided only partial assistance. Even though robotic assistance was unable to move the affected arm as intensely as the less-affected side, subjects were able to move their arm more intensely with robotic assistance than without.

For the Box and Block test the largest improvement trend was for UAT subjects. Given that this test involves grasping blocks and transporting them over a barrier (Mathiowetz *et al.*, 1985), improved performance on the Box and Block test was possibly related to grasping improvements that resulted from reductions in spasticity of the hand and elbow as well as improved ROM in the shoulder. Unfortunately, none of the virtual games involved movements that were similar to the Box and Block test. Therefore it is difficult to relate hand trajectories during robotic training to the Box and Block test. This also gets at a general problem. Even though a rehabilitation robot might collect large amounts of high precision kinematic and force data, it is difficult to draw meaningful comparisons to clinical tests if the movements during robotic training differ substantially from the clinical instrument.

Table II showed a possible improvement in terms spasticity in the hand for all subject groups. However, spasticity in the elbow may have only improved for UAT, but not for BMT. One explanation for this difference might relate to the movements that were imposed on the paretic arm during BMT. While it is true that the stretching of hemiparetic muscles is a recommended exercise for reducing spasticity, it is also important that such stretching be performed at a slow speed (Barnes, 1998; National Stroke Association, 2014). Figure 7 showed that the elbow had a lower proportion of movement compared to the UAT group. Spastic muscles are known to actively resist rapid extension. This may have been the cause for a low proportion of movement in the elbow for BMT. Accordingly, BMT failed to show the same trend of spasticity improvement as was evident for UAT. Thus, if spasticity reduction is a therapeutic

Table III.
Range of motion
in degrees

	Min	Max	Mean	SD
Joint 1, shoulder abduct	11	88	55	20
Joint 2, shoulder flexion	8	106	62	21
Joint 3, shoulder rotation	8	146	32	21
Joint 4, elbow flexion	14	120	71	28
Joint 5, wrist pronation	4	61	23	14
Joint 6, wrist flexion	7	91	38	22
Joint 7, wrist ulnar dev.	11	82	39	20

goal, this data suggests that BMT be avoided. If BMT is used, precautions are possibly needed to ameliorate the deleterious affects of rapid symmetric movements, particularly in the elbow. One solution is to adjust the symmetric control algorithm. This adjustment might limit the joint speeds in the paretic elbow and wrist. However, this would lead to asymmetric rather than symmetric movement. An alternative approach could involve a control scheme whereby the speed is limited in the unaffected arm. For example, providing a viscous sensation would reduce the velocities in both arms while preserving symmetry. Unilateral robotic training has shown promising results in other stroke studies (Krebs *et al.*, 1998; Prange *et al.*, 2006; Kwakkel *et al.*, 2007). With such precautions in place, BMT might have had comparably good results with UAT in terms of reduced spasticity in the elbow.

Possible reductions in grasping strength for UAT are somewhat puzzling. The EXO-UL7 provides no means to explicitly exercise the hand. Instead, subjects simply grasp a handle while performing training. The EXO-UL7 does not measure gripping force in the hand. Therefore, an explanation for reduced grip strength is somewhat speculative. Notwithstanding, a reduction in hand strength has been associated with reduced spasticity (O'Dwyer *et al.*, 1996). Thus, reductions in hand strength might relate to reduced spasticity in the hand.

Given that all three training groups appear to have some improvement in terms of ROM in the shoulder, these results could be interpreted as an indication that ROM in the shoulder was generally more amenable to intervention. ROM was most improved in the shoulder for the BMT. ROM was also improved in the standard care group, but results were mixed for the UAT group. It is not clear how improved shoulder ROM for BMT is explainable by greater cross-talk between the hemispheres of the brain. Indeed, BMT is novel from other types of robotic assistance in that the movements are self-guided by the patient. In this respect, the movements imposed on the paretic arm are literally a reflection of how and when a subject would choose to move their arm. Self-generated BMT did result in more intense training of the paretic arm. Thus, improvement in ROM might have resulted simply from greater intensity, and potentially more natural movements of the paretic shoulder. Finally, lacking more direct measures of neurological activity makes it exceedingly difficult to make decisive conclusions about the effects of robotic training on hemispheric changes in connectivity using kinematic measures alone.

5. Conclusion

The first takeaway from this kinematics analysis is that BMT results in more vigorous training of the paretic arm than does UAT. Second, the intensity calculations presented in this paper provide a quantitative way to assess how vigorously patients train, and which joints are targeted. As was stated previously, the large number of clinical categories being measured renders specific clinical results statistically insignificant. Therefore, even if subjects had better outcomes with BMT than UAT or standard care, the effects were so small that they could not be detected using the population sizes in this study. Moreover, the advantages, or disadvantages of robotic training were too small to make any statistically significant distinctions from standard care. In that light, this pilot study is best thought of as providing guidance for future research and development in the area of rehabilitation robotics. Rather than include a battery of measures that diminish statistical significance, we recommend that similar studies in the future include measures that are more likely to demonstrate a change. By that rational, there were two areas of focus that showed promise. First, future studies

involving rehabilitation robotics might pay particular attention to ROM changes, especially in the shoulder. Second, a dexterity measure, such as the Box and Block test, is a good candidate for assessing improvement. If a virtual game is devised that resembles the Box and Block test (or any clinical test for that matter) that should allow for a more direct way compare clinical outcomes to kinematics measures. Third, and finally, if BST is used, exacerbation of spasticity is a possible area of concern.

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