Normalized Movement Quality Measures for Therapeutic Robots Strongly Correlate With Clinical Motor Impairment Measures

Ozkan Celik, *Member, IEEE*, Marcia K. O'Malley, *Member, IEEE*, Corwin Boake, Harvey S. Levin, Nuray Yozbatiran, and Timothy A. Reistetter

***Abstract*—In this paper, we analyze the correlations between four clinical measures (Fugl–Meyer upper extremity scale, Motor Activity Log, Action Research Arm Test, and Jebsen-Taylor Hand Function Test) and four robotic measures (smoothness of movement, trajectory error, average number of target hits per minute, and mean tangential speed), used to assess motor recovery. Data were gathered as part of a hybrid robotic and traditional upper extremity rehabilitation program for nine stroke patients. Smoothness of movement and trajectory error, temporally and spatially normalized measures of movement quality defined for point-to-point movements, were found to have significant moderate to strong correlations with all four of the clinical measures. The strong correlations suggest that smoothness of movement and trajectory error may be used to compare outcomes of different rehabilitation protocols and devices effectively, provide improved resolution for tracking patient progress compared to only pre- and post-treatment measurements, enable accurate adaptation of therapy based on patient progress, and deliver immediate and useful feedback to the patient and therapist.**

***Index Terms*—Haptic feedback, motor function recovery, movement intermittency, rehabilitation robotics, stroke measures, therapeutic robots.**

I. Introduction

In THIS paper, we present the results of a regression analysis correlating four clinical measures and four robotic (calculated from robot recorded data) measures acquired for nine chronic stroke patients who underwent a one-month program consisting of robotic and traditional constraint-induced movement therapy (CIMT) activities. Fugl–Meyer upper extremity scale (FM), Motor Activity Log (MAL), Action Research Arm Test (ARAT), and Jebsen-Taylor Hand Function Test (JT) clinical scale scores were compared to robotic trajectory error (TE), smoothness of movement (SM), hits per minute (HPM), and mean tangential speed (MTS) measures for a target-hitting task that involved repetitive reaching movements. We show that robotic movement quality measures SM and TE strongly correlate with motor impairment measures FM and ARAT. Our results identify key features that robotic measures should exhibit, such as normalization and evaluation of movement quality rather than movement speed. We believe that these key features should be taken into account in design of a unified set of robotic measures for evaluation of motor function recovery in stroke patients. Such measures are highly desirable in the therapeutic robotics community and are important for accurate tracking of patient motor function improvement at every session, realization of accurate patient progress monitoring in home-based or telerehabilitation and automatic adaptation of robotic therapy task difficulty based on patient progress. In addition, comparisons of the functional gains of patients who undergo different robotic rehabilitation protocols or use different devices will be more reliable and accurate when based on a unified set of robotic measures than when based on heterogeneous robotic measures or pre- and post-treatment evaluations.

Robotics provides numerous opportunities to improve rehabilitation protocols and to lower therapy expenses [2]–[4]. Stroke has a significant social and economic impact on the United States with a $68.9 billion total estimated cost for 2009 [5]. Because of the potential benefits, robotic rehabilitation has been an active field of research for the last two decades. Although various aspects of robotic rehabilitation have been investigated and presented in the literature, a significant effort has been the design of novel therapeutic robots or devices. Early examples of these robots include the MIT-MANUS [3], [6] and MIME [7], [8], both of which were designed for rehabilitation of the proximal upper extremity joints (shoulder and elbow). Due to the success of these early systems, robotic devices for the rehabilitation of distal joints of the upper extremity have also been developed, such as the MAHI Exoskeleton [9], the wrist module of the MIT-MANUS [10], [11] and wrist rehabilitation devices developed by Hesse *et al.* [12] and Andreasen *et al.* [13], to name a few. Most recently, therapeutic robots with

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O. Celik and M. K. O'Malley are with the Department of Mechanical Engineering and Materials Science, Rice University, Houston, TX 77005 USA (e-mail: celiko@rice.edu; omalleym@rice.edu).

C. Boake is with the University of Texas Health Science Center, Houston, TX 77030 USA (e-mail: corwin.boake@uth.tmc.edu).

H. Levin is with Cognitive Neuroscience Laboratory, Baylor College of Medicine, Houston, TX 77030 USA (e-mail: hlevin@bcm.edu).

N. Yozbatiran is with the Department of Physical Medicine and Rehabilitation, University of Texas Houston Medical School, Houston, TX 77030 USA (e-mail: nuray.yozbatiran@uth.tmc.edu).

T. Reistetter is with the Department of Occupational Therapy, East Carolina University, Greenville, NC 27858 USA (e-mail: reistettert@ecu.edu).

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more degrees-of-freedom (DOF) such as Rupert [14] and the RiceWrist [15] that are capable of actuating shoulder, elbow, and wrist joints simultaneously have also been designed.

Far fewer studies have sought to establish a unified set of measures that will enable objective comparison of the efficiency and clinical success of therapeutic robots [16]. According to Hogan *et al.* [4], the challenge is not in the acquisition of kinematic or force data but in extracting clinically useful information. We propose to overcome this challenge by identifying key features for robotic measures that demonstrate strong correlation with clinical measures. Hence, the primary focus of this study is to identify key features for robotic motor function improvement measures that are not protocol or device specific, to present four robotic measures with the desired features and to report their correlations to widely used clinical measures.

Robotic measures have the benefits of being completely objective, capturing quality of movement, and providing patients and therapists with immediate feedback on patient progress [4]. However, robotic measures lack the wide acceptance of clinical measures because they are often device or task specific. Another factor hampering wide acceptance is that robotic measures have not been extensively tested for correlation to widely accepted clinical measures for stroke. Such lack of acceptance by the clinical community limits realization of the important advantages that robotic measures offer. Clinical measures, while reliable and widely accepted, have several drawbacks including variability due to the methods by which the clinical measures are determined, low resolution, subjectivity due to dependence on patient-reported outcomes, and lengthy evaluation procedures that typically limit measurements to pre-, post-, and follow-up sessions [6], [17], [18]. Various robotic measures have been reported in the literature.

Reported examples in the literature include movement smoothness [19]–[21], average movement speed, movement percentage voluntarily achieved by the patient without a robot's assistance [22]–[24], amount of force applied by the patient [4], [17] or error values indicating the difference between the desired position or trajectory and that achieved by the patient [17], [20], [22], [24], [25]. Some of these measures are device or task specific [22]–[24] while others require administration of special evaluation protocols apart from the actual robotic therapy [4], [17], making them difficult to incorporate in the robotic therapy protocol for simultaneous progress tracking and immediate feedback. Reaching movements are common in many of the rehabilitation protocols, and as such, robotic measures based on kinematic data captured during reaching movements have the potential to be readily applicable to a wide range of devices and protocols. Examples of robotic measures applicable to reaching movements are smoothness measures [19]–[21], position or TE measures [17], [20], [22], [24], [25], and average movement velocity measures [21], [22], [24]. With few exceptions, results of the robotic therapy protocols are reported in selected clinical and robotic measures separately, without any correlation analysis between the two.

One study, however, that investigated correlations between robotic and clinical measures was reported by Colombo *et al.* [22]. Clinical trials were completed with a total of sixteen patients who were assigned to one of the rehabilitation devices developed by the group: a one-DOF wrist rehabilitation device and a two-DOF shoulder-elbow rehabilitation device. Three robotic measures were used in the study, namely mean velocity, robot score, and active movement index. Regression analyses revealed a significant and moderate correlation (r =0.53–0.55) between pre- and post-treatment FM scores and the robotic measure scores. Regression analyses for Motor Status Score (MSS) and Medical Research Council (MRC) measures with the same set of robotic measures were found to be inconclusive. Results of the study were limited due to only moderate correlation values with just one of the clinical measures used in the study. Another limitation of the study was that two of the three robotic measures, robot score, and active movement index, were linearly dependent, thereby reducing the number of independent robotic measures used in the study to two. As an extension of this study, the same group examined the correlations of seven robotic measures with the clinical measures FM, MSS, and Motor Power Score [24]. Only one robotic measure showed significant correlation with Motor Power Score, while four robotic measures showed significant correlation with MSS and FM. In all cases, however, the correlations were only weak to moderate (r =0.36–0.58).

Stronger correlations between robotic and clinical measures have been reported in the literature. In [17], Krebs *et al.* defined two robotic measures: a measure of mean force that patients were able to apply in specific arm configurations and a hold radius measure that quantified the total deviation from a hold position as the patient tried to hold a handle in place while a disturbance force was applied. They reported that a strong correlation ($r = 0.85$) exists between Motor Power Scale, a subset of the MRC measure, and the logarithm of the mean force measure and the hold radius measure. Although the obtained correlation was strong, it was limited to a subset of MRC, and data collection with the robot involved specific configurations, acquisition of force data and tasks for evaluation that are not necessarily a part of the rehabilitation protocol itself.

Chang *et al.* [21] recorded the movement trajectories during reaching movements of stroke patients using a motion capture system and were able to compute robotic measures from data collected during the rehabilitation protocol. They showed that only weak to moderate (r =0.37–0.53), albeit significant, correlations exist between two clinical measures (FM upper limb component and Modified Ashworth Scale) and four robotic measures (number of movement units—a nonsmoothness measure— movement time, peak velocity, and normalized jerk score). We believe that the finding of only moderate correlations could be due to the fact that the number of movement units and peak velocity measures do not have sufficient resolution to report useful information related to the impairment. Also, it is likely that the jerk measure suffers from excessive noise due to being numerically differentiated three times, hence losing almost all useful information content.

In a recent study with similar motivations, Bosecker *et al.* [26] reported correlation and linear regression models for clinical measures FM (upper limb component), MSS, Motor Power, and Modified Ashworth Scale. MSS is a clinical measure proposed by the same group as an alternative to FM and has better sensitivity characteristics than FM. Results were reported in terms of both training and validation (prediction) values based on a pool of 111 chronic stroke patients. Robotic measures were composed of eight kinematic macro-measures (based on movement accuracy, speed, and smoothness); seven kinematic micro-measures (calculated from submovement parameters); and four kinetic (force) measures. Linear regression models between all 19 robotic measures and FM measure led to r values of 0.802 in training and 0.427 in validation while for the MSS measure, r values were 0.788 and 0.696 for training and validation, respectively. Kinematic micro-measures were found to improve correlation coefficients only marginally in training and to weaken them in validation. Correlation coefficients of regression models for FM and MSS measures and only kinematic macro-measures were also reported, as well as for Motor Power and kinetic measures. In general, MSS was found to yield higher r values in validation compared to FM, increasing MSS's usability for clinical score predictions.

Similarly, in this paper, we analyze the correlation between four clinical measures and four robotic measures used to assess motor recovery based on data collected from nine stroke patients. The paper is structured as follows. Section II presents the details of the therapy protocol, patient details, clinical measures, robotic measures, and data analysis techniques. Results of the therapy protocol and correlation analyses of clinical measures with robotic measures are presented in Section III. The paper concludes with a discussion of results, contributions and limitations of the study.

II. Methods

A. Participants

A total of nine chronic stroke patients were involved in the hybrid therapy protocol. As in standard CIMT, the patients selected were those who exhibited under-utilization of the affected upper extremity. For inclusion in the study, patients were required to demonstrate enough wrist range of motion to move the joystick and reach the targets. Characteristics of the patients are summarized in Table I. Clinical scores of the patients (see pre-treatment scores in Table II) indicate that the inclusion criteria limited the patients included in the study to those who were only mildly impaired. The therapy was conducted for four weeks except for Patient 1 who underwent therapy for 18 days. Therapy sessions were three days per week (Monday, Wednesday, Friday).

B. Robotic Rehabilitation Device

For the robotic therapy portion of the therapy protocol, the IE2000 haptic joystick by Immersion Inc. was used. The original handle of the joystick was replaced with a conical handle-ball assembly to facilitate patients' grasping as shown in Fig. 1(a). The IE2000 is a backdrivable two-DOF device having a workspace of $\pm 45^\circ \times \pm 45^\circ$ which corresponds to a workspace with arc lengths of 152.4 mm $\times$ 152.4 mm at a 100 mm handle height from the pivot. The joystick has high resolution optical encoders for position sensing that provide 0.036° rotational resolution or a minimum measurable displacement value of 0.02 mm at the same handle height. The maximum force value that can be reflected with the device is 4.94 N at the handle. The inertia and dynamics of the joystick are assumed to be negligible; users primarily feel the forces that define a desired virtual environment generated by customized software. The loop rate for haptic feedback based on impedance control was 1 kHz. OpenGL was used to implement a graphical interface for a target-hitting task. To successfully hit the targets visible on the computer screen, the joystick handle had to be deflected $\pm 27^\circ$ from the vertical position. The testing environment is shown in Fig. 1(b). The choice of IE2000 haptic joystick for calculation of robotic measures is supported by the statement by Hogan *et al.* [4] that backdrivable robotic devices under impedance control provide undistorted measurements of kinematic variables. Additionally, the IE2000 offers the possibility of implementing various operating modes that utilize the device's force-feedback capabilities.

TABLE I
CHARACTERISTICS OF THE PATIENTS. ABBREVIATIONS: BS, BRAIN STEM; HEM, HEMMORHAGIC; MCA, MIDDLE CEREBRAL ARTERY; BG, BASAL GANGLIA; IC, INTERNAL CAPSULE, T, THALAMUS; M, MALE; F, FEMALE; R, RIGHT; L, LEFT

Patient number	Gender	Age (years)	Months since stroke	Side affected	Stroke location
1	M	62	24	R	L BS
2	F	63	12	L	R BG
3	M	62	121	R	L MCA
4	M	65	50	R	L BG and T
5	F	48	20	L	R MCA
6	M	67	14	R	L IC
7	M	57	25	L	R BG
8	M	66	77	L	R Pons
9	M	57	13	L	R IC

TABLE II
THERAPY RESULTS IN FM, ARAT, JT, AND MAL MEASURES. ABBREVIATIONS: P#, PATIENT NUMBER; PRE, PRE-TREATMENT; POST, POST-TREATMENT; p, p VALUE FOR THE MEAN DIFFERENCE BETWEEN PRE- AND POST-TREATMENT RESULTS

P#	FM		ARAT		JT		MAL	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
1	36	41	21	30	301.0	236.0	0.50	2.52
2	23	39	20	33	334.5	181.7	1.81	3.52
3	36	49	32	36	350.7	198.0	1.12	3.63
4	50	58	49	56	156.1	82.0	1.09	4.05
5	43	48	31	35	623.9	263.6	1.78	3.55
6	49	55	51	55	122.6	65.6	1.14	1.95
7	37	33	13	21	1080.0	1011.0	0.39	2.33
8	52	50	56	57	63.7	48.5	1.91	3.71
9	38	47	49	57	251.2	29.7	0.93	3.74
	$p = 0.0097$		$p = 0.0003$		$p = 0.0032$		$p < 0.0001$	

C. Task Description

The task assigned to the patients was to control the position of a pointer in a 2-D workspace to hit targets around a circle. The pointer's position was directly determined by the joystick's position. For patients 1–4, 12 targets were positioned equidistantly on a circle that was centered on the workspace, resembling the positions of numbers on a round clock, as illustrated in Fig. 1(c). The number of targets was found to be redundant and was decreased to eight as part of an update to the software after Patient

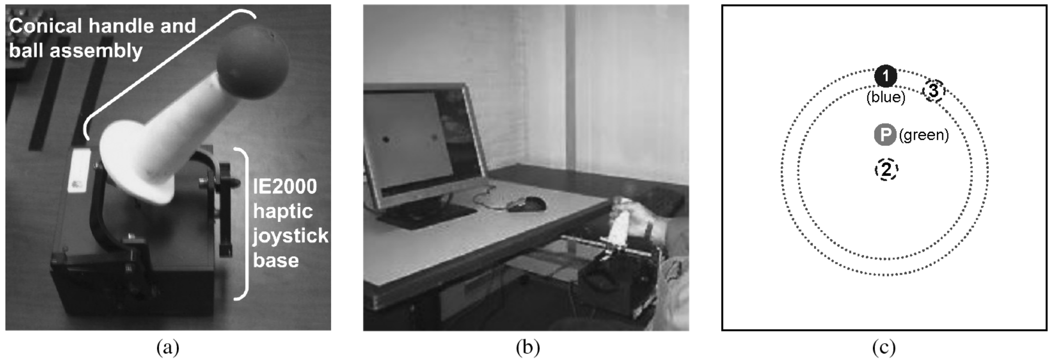

Fig. 1. (a) IE2000 haptic joystick with the replaced handle. The conical shaped handle and ball assembly aimed to provide easier grasping and strapping of the patient to the handle. (b) Patient using the joystick for the target-hitting task (Photograph courtesy of kuhf.org). (c) Graphical interface displayed on the monitor during rehabilitation sessions. Marked are active target (1), the pointer (P), and the next two active targets (2 and 3) that will appear upon successful hits.

4. Hence for patients 5–9, the number of targets around the circle was eight. The active target was displayed until it was successfully hit by the pointer, after which the active target became the center point. Once the joystick was centered, the active target became the next point on the circle in a clockwise direction. A successful movement from the center to the target and back registered two hits. The defined task resembles the task configuration in [19], and the main purpose of the task is to have patients carry out repetitive point-to-point reaching movements. Position data of the cursor were recorded at a sampling frequency of 20 Hz for further analyses for patients 1–4. The sampling frequency was improved and increased to 100 Hz as part of the software update for patients 5–9.

During the therapy sessions, the patient was seated so that the motion required to move the joystick handle comprised forearm pronation/supination and wrist abduction/adduction, with some wrist flexion/extension due to the imperfect alignment between joystick axes and human wrist axes of rotation. In order to prevent patients from completing the required task by compensating with torso movements, an anterior trunk support with zipper (Stayflex Anterior Trunk Support, Standard, Large) attached to the back of the chair was used. Note that this arrangement still allowed use of shoulder and elbow joints, but it did not allow use of any unaffected muscle groups or joints, such as body or torso movements, for compensation.

For patients 1–4, four operating modes were implemented, namely *unassisted*, *constrained*, *assisted*, and *resisted*. In addition to these modes, variations of each of the assisted and resisted modes were used for patients 5–9. The purpose of using various modes was to allow the therapist to adjust the difficulty of the robotic task with regard to the needs, capabilities and progress of each patient. This approach resembles the well-developed behavioral therapy method of "shaping" [27]. Indeed, use of various modes constituted the robotic portion of the shaping exercises under the CIMT protocol (see Section II-D for further details).

In unassisted mode, no force was generated by the joystick, and the movement of the pointer was solely determined by the movement of the patient. Unassisted mode was suitable for gathering and analyzing data that represented a patient's free movement with no external interference. Therefore, in this study, we report robotic measure results recorded in the unassisted mode only. The details of the other modes used in the therapy are not presented in this manuscript, since they are not relevant to the main focus of the study. Information on the other modes can be found in [1].

D. Protocol

The protocol consisted of behavioral techniques and shaping exercises to improve motor function and use of the affected upper extremity. Intensity of therapy was 3-h sessions (including robotic therapy) for three days/week for a duration of four weeks. The behavioral techniques were written contracts to the patient and caregiver, daily monitoring of amount of use of the affected arm and hand outside of therapy, prescribed home practice tasks, and wearing of a restraint on the unaffected upper extremity. The purpose of the restraint, a protective safety mitt to be worn for six waking hours per day, was to encourage use of the affected upper extremity.

During therapy sessions, patients performed shaping exercises using the affected upper extremity, using robotic tasks as well as tasks presented by the therapist. Shaping is a commonly used operant conditioning technique in which the behavioral objective (movement) is approached in small steps of progressively increasing difficulty [27]. Each patient's shaping program consisted of robotic training and tasks selected by the therapist and tailored to address the motor deficits of that individual patient. Therapist-presented tasks utilized commonly available objects such as clothespins, coins, and cups that were manipulated by the fingers of the affected hand. Each shaping task was performed for ten trials, each with a duration of 30–60 s. Results were graphed trial by trial and presented to the patient immediately after each trial. The feedback was based on the time and success rate.

In the robotic therapy component of the rehabilitation program, the therapist determined the operating mode to work in for each trial, based on the patient's needs and progress. Patients 1–4 typically completed two or three 8-min trials (a total of 16–24 min) on each therapy day that formed a daily session. For patients 5–9, daily sessions consisted of 25–40 1-min-long trials and an operating mode was selected by a therapist for each block of five trials.

E. Clinical and Robotic Measures

Four clinical measures were used in this study, namely FM upper limb component, MAL, ARAT, and JT. A total of two therapists participated in the study. Clinical measures were administered by one therapist for patients 1–4, and by another therapist for patients 5–9. Although no independent inter-rater reliability of clinical measures was established for this study, we were confident that both evaluators who performed measuring of upper extremity motor functions had previous experience with the test protocols. In addition both evaluators had a therapist background including extensive experience and knowledge of the nature of stroke impaired arm and hand functions. FM [28] and ARAT [29] have intra- and inter-rater reliability as demonstrated in the literature. JT is a timing based measure and MAL is not administered by the therapist. Hence, inter-rater reliability of therapists is not an issue for these two measures.

The 66-point upper limb component of the FM scale was administered by the therapist. The therapist used a 3-point ordinal scale (0: can not perform; 1: can perform partially; 2: can perform fully) to rate each of 32 items completed by the patient in the test. The FM score was the sum of all ratings with score of reflex activity item doubled [30]. The MAL measure had two components: a 6-point scale for amount of use and another 6-point scale for quality of movement. Patient and caregiver independently rated in both components each item in a list of activities of daily living (ADL). The result was an average of all ratings [31]. In the ARAT scale, there were a total of 19 items grouped in four components: grasp, grip, pinch, and gross movement [32]. Each item was evaluated by the therapist on an integer scale of 0–3. Due to the time-saving design of ARAT scale, if a patient successfully completed the most difficult item in a subscale, it was directly assumed that he succeeded in all less difficult items in that subscale. Similarly, if he failed the easiest item, all items in the corresponding subscale were taken to be failed. Finally, JT was administered with a chronometer. Time in seconds for completing seven different tasks was recorded by the therapist during the test. Total time was the score achieved by the patient [33]. It should be noted that there are fundamental differences among individual clinical measures in this set, with some measuring motor impairment (e.g. FM, ARAT) and others measuring functional use (e.g. MAL, JT). MAL is a structured interview that evaluates by self-report the actual amount and quality of use of the affected upper extremity [31]. In contrast, FM measures the motor recovery of the upper extremity through the assessment of sequential stages of reflexia, synergistic (extension and flexion) patterned movements and finally selective movements [30]. Additionally, some of the measures (like FM) are more widely used and considered to be more reliable and objective compared to others. Our motivation in selecting the mentioned clinical measures has been inclusion of both motor impairment and functional use measures. Two measures of each type have been included to widen the range of measures covered in the study. Nevertheless, our goal was to seek robotic measures that correlate well with all or at least most of these clinical measures, a goal met by TE and SM measures.

Four robotic measures were calculated by postprocessing the data files: TE, SM, average number of HPM, and MTS.

Trajectory Error (TE): The TE measure is defined as a normalized difference between the desired trajectory and the patient's trajectory from one point in the workspace to another. Desired trajectory is always a straight line from the last target to the current target. Absolute values of the deviations from this straight line trajectory during the point-to-point movement were summed to obtain the non-normalized TE value. This value was first divided by the total number of data points during the movement under consideration to normalize it with respect to time. Then it was divided by the distance from the initial point to the end point of the movement in order to obtain spatial normalization. This final value, normalized both spatially and temporally, constituted the final TE value for the movement. With this definition, the TE measure is applicable to any point-to-point movement, regardless of the sampling rate of data acquisition and the traveled distance. The TE value can be interpreted as the average deviation from the straight-line trajectory for each position data point, as compared to the total distance traveled. Since it is a dimensionless value, it is reported as a percentage in this study.

Smoothness of Movement (SM): The SM measure is a correlation coefficient that expresses the correlation between the patient's speed profile and a speed profile utilizing the minimum jerk principle (an optimally smooth speed profile). It was shown in [34] that the speed profiles of healthy subjects' point-to-point movements can be approximated very well with a speed profile that minimizes the squared jerk (time derivative of acceleration) for a movement of equal distance and duration as the actual movement. Emergence and validity of the optimally smooth speed profiles for unconstrained wrist movements was demonstrated in [35]. Also, Huegel *et al.* [36] recently showed that wrist pronation-supination movement speed profiles during point-to-point manipulation of a simulated multimass flexible object were well represented by the minimum jerk profile. Krebs *et al.* [3] showed that stroke patients' speed profiles converge to single-peaked optimally smooth profiles through the recovery process. SM in the minimum jerk sense was one of the five smoothness measures tested in [19]; however, the formulation in [20] and [37] is used here. The speed profile of the patients is derived from the tangential speed of patients' movements. The minimum jerk speed profile on a straight line for each target hit movement was calculated by the equation[1]

$$v_{mj}(t) = \Delta\left(\frac{30t^4}{T^5} - \frac{60t^3}{T^4} + \frac{30t^2}{T^3}\right) \quad (1)$$

where t is time, Δ is distance traveled, and T is the duration of the movement, which was taken to be equal to the time elapsed between two target hits. In order to match the initial points of the actual and the minimum jerk profile, patients' speed profiles were time-shifted. The amount of this shift was determined by the temporal distance between the previous target hit instance

[1]Note that the equation given for the minimum jerk speed profile here differs from the ones in [20] and [37]. Specifically, there is an extra $1/T$ factor in [20] and [37] which does not appear in (1). We believe that this difference is due to typographical errors in [20] and [37], since the minimum jerk speed profile can be obtained by taking the derivative of the minimum jerk position profile given in [34], which will not have the extra $1/T$ factor. Also notice that this extra factor will not affect the calculated SM values, since the measure itself is defined as a correlation coefficient that is invariant to linear transformations on either of its input variables

and the minimum value in the first half of the actual speed profile. This method is similar to the one mentioned in [20] with some minor differences in calculation of T and data shifting procedure. The correlation coefficient ρ is calculated by

$$\rho = \frac{\Sigma\left[(V_{\text{pat}} - \overline{V}_{\text{pat}})(V_{mj} - \overline{V}_{mj})\right]}{\sqrt{\Sigma(V_{\text{pat}} - \overline{V}_{\text{pat}})^2 \Sigma(V_{mj} - \overline{V}_{mj})^2}} \qquad (2)$$

where V_{pat} is the movement speed of the patient, $\overline{V}_{\text{pat}}$ is the mean movement speed of the patient, V_{mj} is the minimum jerk speed profile, $\overline{V}_{mj}$ is the mean minimum jerk speed, again following the formulation given in [20]. Since linear scaling of either speed profile does not alter the correlation coefficient, normalization of speeds with respect to peak speed in the profiles were left out, for clarity and simplicity of the definition of the measure. The correlation coefficient takes values between 0 and 1, where 1 indicates perfect correlation with the optimally smooth speed profile and 0 indicates no correlation. During data processing, negative ρ values occasionally calculated for individual movements, which implied negative correlation, were set to zero. Similar to the TE measure, SM can be calculated for any point-to-point movement and is dimensionless since it is a coefficient designating the correlation of the actual speed curve demonstrated by the patients to the optimally smooth speed curve for a movement having the same duration and distance as the actual movement.

Average Number of Hits per Minute (HPM): An average of the number of hits for a 60-s duration constituted the HPM measure. The HPM measure is more closely related to the task assigned to the patients and was the only robotic measure available to the patients instantly during the robotic rehabilitation since patients were told the number of hits they achieved at the end of a session. Due to its definition, HPM is similar to a mean speed measure and is the only nonnormalized robotic measure in this study. We have used a normalized MTS measure in the study as well, as defined next.

Mean Tangential Speed (MTS): Several studies in the literature have used mean speed as a robotic motor function improvement measure for stroke patients [21], [22], [24]. Similar to the definitions in these studies, we defined the MTS measure as the mean movement speed demonstrated for each point-to-point movement trial. Calculating the mean speed in the tangential speed domain gives credit to the patient for moving in any direction, even though the movement may not be towards the target. MTS measure is spatially normalized by dividing the obtained scores by target distance; hence it is reported in the units of [1/s]. Similar to the HPM measure, the MTS measure demonstrates the overall speed of the patient in the task rather than the quality of the movement.

F. Robotic Measures in Relation to Activities of Daily Living

The TE and SM measures serve as objective assessments of movement quality. The TE measure evaluates the patients' performance of tracking straight line target trajectories, while the SM measure compares the speed profile of the patients' movements with the speed profiles observed in healthy people's movements. In addition to serving as a scoring method immediately available to the patient and the therapist during therapy, the HPM measure is an indication of how fast a patient is able to move the affected upper extremity, similar to MTS measure. In contrast to TE and SM, HPM and MTS are motor recovery measures in the speed domain based on the fact that stroke patients demonstrate compromised overall movement speed as compared to healthy individuals [38].

A low TE implies the ability of precisely following planned trajectories and adeptness in ADL that involve reaching and pointing. Similarly, a high SM implies smooth and nonjerky/nonintermittent movements and would indicate proficiency in ADL that involve carrying an object and handling delicate objects. Both TE and SM measures are closely related to the coordination of movement which is a fundamental component of a skilled, fine movement. A high HPM or MTS score indicates well controlled overall movement speed and would transfer to faster movements in ADL. It should be noted that for the results reported in this paper, the ADL in the preceding discussion would be limited to those that involve mainly wrist movements due to the joystick hardware we have used. However, the highlighted points remain valid for a broader set and range of movements since the measures can be calculated for any point-to-point movement, though validations under additional joint movements (shoulder, elbow, etc.) are not included in this study.

In summary, all four measures can be said to demonstrate how stroke patients' movements deviate from healthy people's movements. Based on sampled data collected from the movements, they provide practical, fast, direct and objective evaluations of movement quality (TE and SM) and speed (HPM and MTS).

G. Statistical Analyses

We conducted differential significance analyses to determine whether the patients showed a significant motor function improvement with respect to the clinical measures. To be able to make an overall comparison of these results with those recorded in robotic measures, we completed similar analyses using robotic measures. Daily average values of SM, TE, and HPM measures were regressed on the number of days to reveal motor function recovery trends of individual patients. The absolute number of days instead of the number of therapy days was preferred by taking the CIMT activities on the off-therapy days into consideration. Significance of the slopes, hence the trend in the motor improvement, was determined. Slope values were also recorded to be able to identify the patient that demonstrated the strongest trend.

Regression analyses were used to investigate the correlation between the clinical and the robotic measures, the main objective of the study. The pre-treatment and post-treatment FM, ARAT, JT, and MAL scores of the patients were paired with the corresponding robotic measure results that were temporally the closest to the clinical evaluations (the first day and the last day robotic therapy scores in the unassisted mode). Regression analyses were carried out using the paired data sets, and the set of parameters summarized were the correlation coefficient r (Pearson's r) and the p value that represents the significance of the slope of the linear fit line. A significant slope indicates that the correlation coefficient r is also significant; i.e., there is

TABLE III
PRE- AND POST-TREATMENT RESULTS IN ROBOTIC MEASURES TE, SM, HPM, AND MTS AND THE INDIVIDUAL RESULTS OF THE REGRESSION ANALYSES OF DAILY AVERAGE ROBOTIC SCORES VERSUS DAYS. * DENOTES SIGNIFICANT TRENDS IN REGRESSION ($p < 0.05$). ABBREVIATIONS: P#, PATIENT NUMBER; N, NUMBER OF DATA POINTS USED FOR REGRESSION; β, SLOPE OF THE REGRESSION LINE; p, p VALUE OF THE PAIRED-SAMPLE ONE-TAILED T-TEST FOR DIFFERENCE BETWEEN PRE- AND POST-TREATMENT SCORES

P#	N	TE			SM			HPM			MTS		
		Pre	Post	β	Pre	Post	β	Pre	Post	β	Pre	Post	β
1	8	11.6	10.8	0.034	0.406	0.455	0.001	84.8	111.1	1.177	2.58	3.53	0.057*
2	9	14.8	12.1	-0.056	0.224	0.273	0.003	32.8	45.8	0.627*	1.13	1.26	0.011
3	13	10.3	7.5	-0.099*	0.159	0.396	0.007*	35.7	77.8	1.349*	1.19	1.91	0.022
4	15	5.9	6.6	-0.016	0.457	0.695	0.007*	55.5	116.8	1.931*	1.06	2.50	0.046*
5	12	10.0	10.0	-0.084*	0.417	0.447	0.006*	51.9	75.7	1.532*	1.32	1.96	0.033*
6	12	5.4	6.0	-0.040	0.301	0.425	0.006*	57.1	71.7	0.835*	1.28	1.58	0.012*
7	12	17.6	9.4	-0.336*	0.068	0.371	0.013*	12.5	45.6	1.226*	0.75	1.13	0.011
8	10	9.6	4.7	-0.192*	0.442	0.714	0.013*	63.6	88.5	1.497*	1.78	1.60	0.005
9	12	10.4	5.3	-0.113*	0.202	0.295	0.002*	52.7	39.2	-0.275	1.33	0.76	-0.014*
		$p = 0.0173$			$p = 0.0013$			$p = 0.0033$			$p = 0.0034$		

a significant correlation between the two variables. Regressing four clinical measures on four robotic measures resulted in a total of sixteen correlation results.

III. RESULTS

Clinical measure results for the patients are summarized in Table II. The mean difference between post- and pre-treatment scores for all measures is found to be significant ($p < 0.05$) on a one-tailed paired-sample *t*-test. Based on the p values, it can be said that motor recovery gains were more pronounced in MAL and ARAT scores. Similarly, results of the therapy protocol in robotic measures are summarized in Table III. Again, for all measures, the mean difference between pre- and post-treatment scores are significant. The SM measure indicated a stronger gain in motor function for the group compared to other measures. In the same table, slope values (β) for individual motor recovery trends based on regression of daily average scores on days are reported, and significant slopes are marked with an asterisk (*). The robotic measure results were similar and comparable for both groups of patients (1–4 and 5–9)[2]. The column labeled N lists the number of data points used for the corresponding regression. A general decreasing trend (negative slope) was observed for the TE values (decreasing error) while trends were positive for SM, HPM, and MTS (increasing movement smoothness, hit rate, and MTS), except for Patient 9. The strongest trends based on the slope values were observed for Patient 7 with respect to the TE measure, for Patients 7 and 8 with respect to the SM measure, for Patient 4 with respect to the HPM measure and for Patient 1 with respect to the MTS measure.

Correlation coefficients resulting from the correlation analyses of clinical measures with robotic measures are summarized in Table IV, with significant correlations marked with an asterisk (*). The TE and SM measures have significant correlation with all four clinical measures, while the HPM measure has significant correlations only with the FM and JT measures. The MTS measure fails to show significant correlation with any of the clinical measures. Regressions of FM-TE, FM-SM, and ARAT-TE that have high and statistically significant r values are depicted in Fig. 2 together with the regression lines.

[2]Daily average robotic measure scores versus days plots with trendlines for all patients are not given here due to space limitation; however, results are available at http://mahilab.rice.edu/sites/default/files/rehab_supplemental.pdf.

TABLE IV
RESULTS OF THE CORRELATION ANALYSES OF FM, ARAT, JT, AND MAL MEASURES ON TE, SM, HPM, AND MTS MEASURES (SEE TEXT FOR FULL VERSIONS OF ABBREVIATIONS). CORRELATION COEFFICIENT (PEARSON'S) r IS LISTED. * DENOTES SIGNIFICANT CORRELATION ($p < 0.05$). CORRELATION PLOTS FOR THE HIGHLIGHTED PAIRS OF MEASURES ARE PRESENTED IN FIG. 2. NOTE THAT IMPROVEMENT IS REPRESENTED BY AN INCREASE IN ALL MEASURES EXCEPT TE AND JT

	TE	SM	HPM	MTS
FM	-0.74*	0.64*	0.54*	0.22
ARAT	-0.83*	0.51*	0.37	0.00
JT	0.63*	-0.49*	-0.53*	-0.32
MAL	-0.49*	0.57*	0.46	0.21

IV. DISCUSSION

Although there have been numerous studies on the design and testing of novel therapeutic robots, an effective method for objective assessment and comparison of such devices is yet to be determined. The potential prospects of robotic rehabilitation include home-based rehabilitation systems, remote supervision by therapists, and automated adaptive rehabilitation programs. For all of these opportunities to be embraced, a unified set of robotic motor recovery measures with known correlation to clinical measures is highly desirable.

This paper identifies key aspects for such unified robotic motor recovery measures by analyzing the motor function improvement scores of nine chronic stroke patients who underwent a hybrid therapy program, utilizing four clinical measures (FM, ARAT, JT, and MAL) and four robotic measures (SM, TE, HPM, and MTS). In this paper, we do not explore directly the efficiency or the success of our hybrid therapy protocol. Neither do we propose a finalized or complete set of unified measures. Rather, we use our clinical data to compute correlations between robotic and clinical measures and indicate important properties that such measures should exhibit for strong correlation with clinical measures.

In the following sections, we review the implications due to use of a haptic joystick, summarize the overall outcome of the therapy program, and use the motor recovery gains as a means of identifying the relationships between clinical and robotic measures. We subsequently discuss the main results of the study, correlations of clinical and robotic measures and present the limitations of the study. Finally, we highlight the contributions of the study.

A. Use of a Haptic Joystick for Robotic Rehabilitation

There are a number of examples of force-feedback joysticks being used for rehabilitation applications. The focus in a number of such studies has been to address the need for low-cost and home-based rehabilitation systems. For example, Reinkensmeyer *et al.* [39] introduced the Java Therapy system that utilized a commercially available low-cost force-feedback joystick and web-based therapy games that provided feedback to the patient on his/her progression. Ellsworth and Winters [25] also used a commercial joystick after revising it to improve range of motion and have force-feedback capabilities. A second phase of the study was conducted to create three-DOF movement capabilities [40]. Differing from the previous studies, we selected a commercial haptic joystick for rehabilitation because of its ability to precisely capture position data that are later used to calculate robotic motor improvement measures.

Use of the haptic joystick as the only hardware in the study may cause one to question the extension of results to other devices. The definitions of the normalized robotic measures in this study are formulated in such a way as to be potentially applicable to various hardware and protocols, as long as point-to-point movements are involved. Here, we do not explicitly provide proof or validation of the measures under use with different devices, but rather view this as a point for future work. That being said, we do believe that normalization is a crucial feature of any robotic measure.

Another implication of using the joystick for therapy and evaluation is the limitation of the movements mainly to wrist joints. Although it is possible to use the robotic measures defined in this study for movements involving any number of joints, they were calculated mainly based on wrist movements. Conversely, the clinical measures used in this study were not necessarily restricted to certain joints. Rather they involved activities pertaining to most of the joints of the upper extremity. Nevertheless, the results clearly indicate that significant moderate to strong correlations exist between the TE and SM measures and the clinical measures. This result implies that application of the TE and SM measures to tasks that involve the full upper extremity or that more closely resemble the tasks administered in clinical evaluation protocols may lead to even stronger correlations.

B. Agreement Between Clinical and Robotic Measures

As reported in Table II, patients exhibited a significant motor function improvement, regardless of the clinical measures used for assessment. This finding is in agreement with the significant improvements indicated by all robotic measures, as summarized in Table III. It should be noted that there are several individual insignificant slopes for the regression of the robotic measures on days; however, *t*-tests for the complete group of patients indicate significant overall improvements for all measures.

Clinical and robotic measure results in our study are found to be mostly in agreement. However, the degree of improvement of any particular participant differs based on the scale used. As a result, significant changes observed in one measure do not always appear as pronounced in other measures. This result is in agreement with the results obtained by Colombo *et al.* [24]. Colombo *et al.* reported the difficulty in defining a single measure that would be valid and accurate for all levels of impairment, and said that some robotic measures will always have to be used as complementary to existing objective clinical measures. It should be noted that the majority of the patients included in our study were only mildly impaired, and this constitutes a limitation on the generalizability of our results to patients with a broader range of impairment levels. The measures SM and TE both required successful completion of reaching movements, which already requires existence of a certain level of motor function. In this respect, the MTS measure can be used for more compromised cases, although its correlation with clinical measures obtained in this study is poor. Identification of robotic measures that allow objective evaluation of motor function in moderate to high level of impairment is a topic not addressed in this study and constitutes a potential future direction for work. One possibility is to forego the advantage of real-time evaluation during therapy and instead use special evaluation sessions with robotic devices, examples of which are given in [4] and [17], a choice which may be more suitable to severely impaired patients.

C. Correlation of Clinical and Robotic Measures

In Table IV, measures quantifying movement quality, TE and SM, demonstrate significant and moderate to strong correlations with all clinical measures. In contrast, correlations of movement speed based measures, HPM and MTS, with clinical measures mostly fail to show significance, and correlations range from none at all (MTS-ARAT) to moderate (HPM-FM). Therefore, we conclude that one key feature for a robotic measure to have strong correlation with clinical measures is focus on movement quality rather than on speed. It is reported in the literature that the ARAT and FM scales are usually well correlated with each other [32]. Our findings are in agreement with the literature; robotic measures that are strongly correlated with the FM measure are also strongly correlated with the ARAT measure.

An important result is the strong correlation between the TE and FM measures ($r = 0.74$) and between the TE and ARAT measures ($r = -0.83$). TE is therefore a stronger candidate as a unified robotic measure of motor impairment than SM is. We consider this to be an interesting result since in our prior analyses the TE measure was defined in a non-normalized fashion. This finding indicates the importance of normalization as another key aspect in defining robotic motor recovery measures. In addition to leading to stronger correlations with clinical measures, normalized robotic measures have the distinct advantage of being applicable to different rehabilitation protocols and devices. This feature is important for objective and effective comparison of outcomes of different therapeutic robots and protocols.

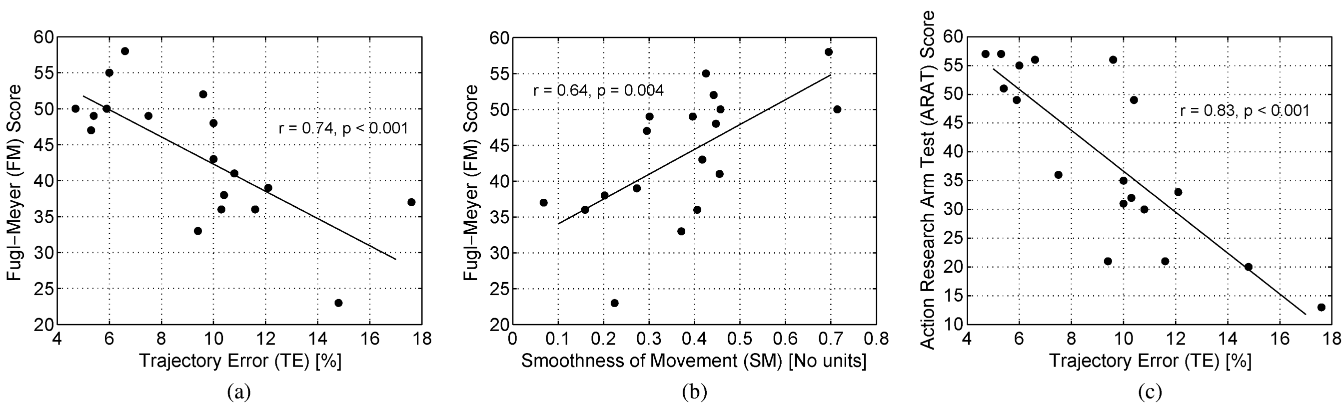

Fig. 2. Regression plots for clinical measures FM, ARAT, and robotic measures TE, SM. Correlation coefficients between two types of measures and the p value of the correlation coefficients are given. Each patient is represented by two points (pre- and post-treatment scores). (a) Strong and significant correlation exists between FM and TE measures. (b) There is a moderate and significant correlation between FM and SM measures. (c) There is a very strong and significant correlation between ARAT and TE measures.

The strongest correlations were observed between the SM and TE robotic measures and the ARAT and FM clinical measures, which are measures of motor impairment. We conclude that the SM and TE measures therefore can capture the degree of motor impairment; though not functional use. We found only weak to moderate correlations between our robotic measures and clinical functional use measures (JT and MAL). Therefore, we conclude that robotic measures based on reaching movement data are not likely to exhibit strong correlation with clinical measures of functional use, and that in order to identify such correlations, one may need to define robotic measures that replicate or approximate administering conditions and methods of functional use measures.

The poor correlation of our MTS measure with the selected set of clinical measures is an important result demonstrating that the definition of robotic measures that will significantly and strongly correlate with clinical measures is not a trivial task. Significant and moderate correlations of mean speed measures with clinical measures were reported in the literature [22], which are comparable to our observed correlations using the HPM measure. However, the normalized MTS measure showed no correlation to weak correlation with the clinical measures, leading us to conclude that mean speed measures are inferior candidates for broadly applicable robotic measures compared to movement quality measures, especially in the context of high correlation with clinical measures. Although mean speed measures are relevant to feedback given to patients in shaping exercises, the fact that movement speed is in general not explicitly part of clinical measures leads to only weak correlations. Nevertheless, robotic devices enable recording of variables that are not explored by the clinical measures.

The significant correlations observed with our SM, TE, and HPM measures are in agreement with the results obtained by Colombo *et al.* [22]. We have observed much higher correlation coefficient values, between 0.49–0.83, with the TE and SM measures defined in this study, compared to 0.53–0.55 reported in [22], 0.37–0.58 reported in [21], and 0.37–0.53 reported in [21]. We were not able to match the correlation coefficient of $r = 0.85$ reported by Krebs *et al.* [17], but it should be noted that they applied a specific robotic evaluation protocol that involved non-normalized force measurements. In contrast, the TE and SM measures defined in our study are normalized kinematic measures (requiring only position data recording) and are applicable to any reaching movement. Our approach can be implemented in most existing robotic rehabilitation devices in a straightforward manner. Similar arguments hold for results of Bosecker *et al.* [26], where they used linear regression models with up to 19 robotic measures, including force and kinematic measurements requiring both reaching and circle drawing tasks. Taking only the movement smoothness measure (best performing measure in their set) into account, they reported r values of 0.62 for FM and 0.56 for MSS with a training data set.

Based on the moderate to strong correlations reported in Table IV and Fig. 2, we believe that it is feasible to identify a set of broadly applicable robotic measures using correlations between robotic and clinical measures. Obviously, high scatter in the data in Fig. 2 would indicate diminished correlation coefficients and feasibility. One source of scatter in our data set is pre-treatment scores of Patient 2 ($\text{FM score} = 23$), who is the only more than mildly impaired patient in the group. An additional unavoidable source for scatter is the range of types and locations of stroke for our participant group (see Table I).

D. Implications and Application Potential of Correlations

Strong correlations suggest that our robotic measures may be used to provide immediate and useful feedback on and continuous monitoring of motor improvement, and to establish a better framework to compare the outcomes of different robotic rehabilitation programs. Strong correlations ensure that if robotic measures are to be provided as feedback to patients during therapy, they must be well grounded in widely accepted clinical assessment techniques. For example, in our study we show that speed-based measures do not correlate strongly with clinical motor impairment measures. Therefore, a participant could be moving very quickly but not improving in their quality of movement, and feedback about their movement speed, intended to be motivational regarding their rate of progress, may not translate to gains in terms of clinical measures such as FM and ARAT over the course of therapy.

We have used an actuated rehabilitation device in our protocol, but we have analyzed robotic measures in an unassisted mode. Hence our results are also relevant and important from the perspective of unactuated rehabilitation devices. Because these devices have sensors but no actuators, they cannot provide actively intervening assistive or resistive forces. Despite the absence of actuation, movements of the patients can still be precisely sampled and recorded. An example of these devices was reported by Sanchez *et al.* [18]. Another possibility is the use of motion capture systems to record marker trajectories during reaching movements to evaluate the extent of motor impairment, as demonstrated by Chang *et al.* [21]. Since both approaches allow recording of movement data, they can serve as tools for calculating TE and SM robotic measures, which we have shown to be strongly correlated to FM and ARAT scores. Unactuated rehabilitation devices or affordable motion capture systems can provide an inexpensive and practical way of conducting clinically correlated assessments. Actuated backdrivable therapeutic robots can readily be used to take advantage of these findings by simply recording data in an unassisted mode.

We believe that the results discussed here contribute to the efforts of defining robotic motor recovery measures that are well correlated with clinical measures. We have identified two key features for such robotic measures: normalization and focus on movement quality.

We consider the results of our study to be evidence for the feasibility of the challenging task of identifying reliable robotic measures that may also be used to predict clinical measures such as FM, ARAT, or JT. However, larger data sets would be required to accomplish this goal, and obtained regression relations would be required to be validated on additional data sets to ensure reliable estimation capability. Additional data and clinical trials are needed to generate more robust and accurate correlation charts between clinical and robotic measures, which will constitute a focus for future studies. Also of interest for future work is to test how the validity and strength of correlations are affected by external assistive and resistive forces that are usually present in robotic rehabilitation protocols.

SM and TE measures defined here are available for use with a wide range of robotic rehabilitation devices and protocols and can be calculated for any point-to-point reaching or pointing movement. We have shown that SM and TE are strong candidates for a unified set of robotic measures that will enable objective evaluation and comparison of robotic rehabilitation programs and devices, while maintaining clinical relevance due to their correlation with widely accepted clinical measures.

V. Conclusion

This study reports correlations of four clinical measures with four robotic measures based on data from nine chronic stroke patients who underwent a robotic and CIMT rehabilitation protocol. TE and SM robotic measures and four clinical measures correlate significantly with moderate to high correlation coefficient values (Pearson's $r = 0.49$–0.83). We conclude that TE and SM measures have the potential to serve as important robotic measures that are well correlated with the FM and ARAT scales, well known, widely used and reliable clinical measures. We determined that normalized robotic measures that capture quality of movement are most suitable for use with different devices and protocols and that these measures also exhibit strong correlations with clinical measures.

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Ozkan Celik (M'10) received the B.S. and M.S. degrees in mechanical engineering from Istanbul Technical University, Istanbul, Turkey, in 2004 and 2006, respectively. He is currently working toward the Ph.D. degree at the Mechanical Engineering and Materials Science Department, Rice University, Houston, TX.

He is currently a Research Assistant at the Mechatronics and Haptic Interfaces (MAHI) Laboratory. His research interests include human sensorimotor control system, motor adaptation and learning, robotic rehabilitation, mechatronics, robotics, and haptics.

Mr. Celik was the recipient of a young researcher travel award at the IEEE International Conference on Rehabilitation Robotics (ICORR) in 2009

Marcia K. O'Malley (M'03) received the B.S. degree from Purdue University, West Lafayette, IN, and the M.S. and Ph.D. degrees from Vanderbilt University, Nashville, TN, all in mechanical engineering.

She is an Associate Professor in the Mechanical Engineering and Materials Science Department at Rice University, Houston, TX. Her research interests include haptics and robot-assisted rehabilitation.

Dr. O'Malley received the George R. Brown Award for Superior Teaching, has been named an ONR Young Investigator, and is the recipient of an NSF CAREER Award. She is an Associate Editor for the IEEE TRANSACTIONS ON HAPTICS and the ASME/IEEE TRANSACTIONS ON MECHATRONICS.

Corwin Boake received the Ph.D. degree in clinical psychology from the University of Louisville, Louisville, KY. He completed his internship at the University of Oklahoma Health Sciences Center, Oklahoma City, OK.

He is an Associate Professor of Physical Medicine and Rehabilitation at the University of Texas-Houston Medical School and an Adjunct Associate Professor at Baylor College of Medicine. He is also a Neuropsychologist at The Institute for Rehabilitation Research-Memorial Hermann. He completed postdoctoral fellowships in neuropsychology at the University of Houston and the New York University Medical Center. His research interests are stroke rehabilitation, spinal cord injury rehabilitation, and traumatic brain injury rehabilitation.

Harvey S. Levin is a Professor in the Departments of Physical Medicine and Rehabilitation, Neurology, and Neurosurgery, Baylor College of Medicine. He is also Director of Research in the Department of Physical Medicine and Rehabilitation. His research is concerned with the neurobehavioral recovery and neuroplasticity after acquired brain injury. He is also engaged in clinical trials for treatment of patients sustaining traumatic brain injury.

Nuray Yozbatiran received the B.S. degree in physical therapy from Hacettepe University, Ankara, Turkey, in 1991 and the M.S. and Ph.D. degrees from Dokuz Eylul University, Izmir, Turkey, in 1995 and 2000, respectively.

She is a Research Instructor at the Department of Physical Medicine and Rehabilitation at the University of Texas Health Science Center, Houston. From 2000 to 2005 she taught and coordinated research in neurorehabilitation at Dokuz Eylul University. From 2005 to 2007 she held a postdoctoral fellow position in the Neurology Department, University of California, Irvine, and another postdoctoral fellow position from 2007 to 2009 in the Department of Physical Medicine and Rehabilitation, University of Texas Health Science Center, Houston. Her research interests include motor recovery and rehabilitation in stroke and spinal cord injury and robotic rehabilitation.

Timothy A. Reistetter received his B.S. degree in psychology from Old Dominion University, Norfolk, VA, in 1989, the M.S. degree in occupational therapy from Shenandoah University, Winchester, VA, in 1996, and the Ph.D. degree in occupational therapy from Texas Woman's University, Houston, in 2004.

His clinical experience has been primarily adult neuroscience, stroke and brain injury rehabilitation. He was a research project specialist for the Brain Injury and Stroke Program at The Institute for Rehabilitation and Research from 2003 to 2006. He is an Assistant Professor in the Occupational Therapy Department at East Carolina University, Greenville, NC, where he started an upper extremity motion laboratory to study the effects of spasticity and movement disorders on functional abilities. Additionally, he is an Assistant Professor at the University of Texas Medical Branch, Galveston, in the Division of Rehabilitation Sciences and an NIH K12 scholar focusing on rehabilitation outcomes and functional status following stroke.