Using Socially Assistive Robotics to Augment Motor Task Performance in Individuals Post–Stroke

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***Abstract*—This paper presents an application of a socially assistive robotics (SAR) system to hands-off post–stroke rehabilitation. We validate the technical feasibility and efficacy of our system in guiding, motivating, and administering an upper extremity rehabilitation task. The robot, which consists of a humanoid torso on a mobile base, monitors user performance on a wire puzzle task through a wearable inertial measurement unit and signals from the puzzle. Smoothness of stroke-affected limb movement is used as the evaluation metric. Five adults of mild to moderate functional ability in the chronic phase of stroke recovery interacted with our SAR system over three separate days. The inertial data from the five participants were analyzed using frequency domain techniques. Subsequently, the amount of power in frequency bands corresponding to voluntary (0.1 to 2Hz) and involuntary motion/jerk (4 to 8Hz) was evaluated. We found that, in adults of mild severity (Upper Extremity Fugl–Meyer Assessment scores greater than 40), the motion becomes smoother (the amount of jerk is reduced) over 3 days of task practice. In adults of moderate motor severity (scores below 40), the motion became less smooth. This may indicate that the combination of our task and SAR system is better suited for individuals with higher functional ability, and needs augmentation in order to aid those of lower functional ability levels.**

I. Introduction

Socially assistive robotics (SAR) has emerged as a promising set of methodologies for the provision and administration of motivation, encouragement, and rehabilitation for those suffering from cognitive, motor, and/or social deficits [1]. The intersection of assistive robotics and socially interactive robotics, SAR focuses on hands–off interactions with robots in therapeutic settings. Using embodiment, emotion, dialog, personality, user models, socially situated learning, and intentionality, SAR robots can manipulate and guide interactions with users in order to achieve desired behavioral outcomes [2]. This methodology has shown promise for a number of domains, including tutoring, emotional expression, daily life assistance, and physical therapy [1] [3] [4].

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In the domain of physical therapy, SAR is particularly promising for stroke rehabilitation. Stroke affects a large percentage of the population worldwide, with over 9 million people affected annually, many of whom go on to live with motor disabilities [5]. This population also often suffers from associated cognitive deficits. Therapeutic interventions for stroke typically consist of intense one–on–one practice with a trained clinician, focusing on specific real–world tasks modeled on activities of daily living (ADLs). Such task–specific practice can lead to recovery from motor task deficits. However, the number of individuals affected by stroke is outpacing the number of trained clinicians and medical resources, and has produced a growing gap between the necessary amount of therapy and the amount that can be provided with the current standard of care.

This is where SAR can serve a valuable role. Given the determination of a deficit and an associated rehabilitation regimen by a trained clinician, SAR can be used as a methodology and a therapeutic tool for the guidance and provision of an intervention. Our past work has evaluated the technological feasibility and acceptance of SAR robots in the post–stroke population [6] [7].

In this paper, we present our SAR framework as a proof of concept for the provision of a therapeutic intervention to affect changes in motor function. We use motion smoothness as the kinematic measure of motor function. This metric is well established; it has been used by Elble et al. as a measure of motion quality [8] and is employed by physical therapists as one of the sub parameters of motion quality assessment in standard tools such as the Wolf Motor Function Test (WMFT) and the Test d'Evaluation des Membres Supérieurs de Personnes Agées (TEMPA) [9] [10].

We begin by providing some background on rehabilitation robotics. Next, we describe our system and the methods used. We then present our data analysis, algorithms, and results, and finally offer discussion and conclusions regarding the research outcomes.

II. BACKGROUND

A. Rehabilitation Robotics

The field of rehabilitation robotics has benefited from recent advances in sensing and actuation. The general approach in this field has been to create orthoses that physically interact with individuals with motor deficits. Lower extremity (LE) devices such as the LOKOMAT® [11] and ALEX (active leg exoskeleton), designed for gait retraining, apply forces to the leg sections in an attempt to retrain healthy gait patterns [12]. Upper extremity (UE) devices include the ARM Guide, developed by Reinkensmeyer et al., to help individuals target objects using the affected limb [13]. The ARMin III system, developed by Reiner et al., is an exoskeleton–like robot using a design based on human shoulder dynamics, also targeted for stroke rehabilitation [14]. Another UE training system, developed by Schweighofer et al., allows users to practice functional tasks modeled on activities of daily living such as closing a door or turning a doorknob [15].

The maturity of the rehabilitation robotics field is also indicated by the fact that devices have been tested in clinical trials. Lo et al. utilized the MIT Manus robot in a large clinical trial [16] and demonstrated that the robot could produce clinical outcomes similar to those obtained using dose equivalent human–administered therapies.

B. Socially Assistive Robotics

The field of socially assistive robotics (SAR) is a newer development and is defined as the provision of assistance through social (not physical) interactions with robots [1]. A SAR robot uses non–contact verbal and non–verbal feedback, coaching, and encouragement to guide a user during the performance of a task. SAR systems can demonstrate task goals, monitor the user, and provide extrinsic performance feedback. The lack of physical contact means there are a minimum of safety concerns. Further advantages include lower costs and increased accessibility relative to contact–based robot systems. A SAR interaction can take place in a multitude of environments, including the laboratory, the clinic, and the user's home.

Our past work has shown the efficacy of SAR in a variety of domains, including elder care [17] [18], Autism Spectrum Disorders [19], stroke assessment [20] [21], and stroke rehabilitation [7]. A key advantage of non–contact SAR over contact–based robotics in the stroke population is that individuals can use the more affected limb in the types of meaningful, unconstrained, functional tasks encountered in daily life. This approach also has the ability to provide personalized therapeutic interactions that can complement the therapist. We view SAR as complementary to contact–based rehabilitation systems, with its usefulness being especially targeted toward post–acute stages of stroke rehabilitation, which have been shown to potentially continue life-long.

In the following, we describe the implementation of our SAR system for intense, task–specific training for post–stroke rehabilitation and present preliminary results.

Fig. 1. Bandit, the humanoid robot used in our experiments.

Fig. 2. The physical setup for the SAR rehabilitation experiments: Bandit humanoid robot, wire puzzle, wands, and wearable motion sensor.

III. SAR SYSTEM FOR MOTOR TASK PRACTICE

A. Physical Setup

The physical setup for our SAR system consisted of a humanoid robot torso, an instrumented wire puzzle, and wearable sensors. The robot used in our experiments is the humanoid Bandit, developed at the USC Interaction Laboratory in conjunction with BlueSky Robotics (Figure 1). We have used Bandit in a variety of SAR interactions in the past [17] [18] [6]. In this study, Bandit was used to guide participants during the performance of a wire puzzle game (Figure 2). Participants were seated at a desk facing Bandit and the puzzle and had a selection of wands; the goal was to guide the ring at the end of each wand along the wire puzzle without contacting the wire (Figure 3). Bandit used two different "coaching styles:" in one, Bandit instructed the participants which wand to use, while in the other, they chose the wand themselves. Task difficulty was controlled by appropriately selecting wands with smaller or larger diameters, and puzzles with lower or higher complexity (wire curvature). A Phidget InterfaceKit was used to electrically instrument the puzzles; this allowed us to collect error (total number of contacts between the ring and puzzle) and movement time data.

Participant arm motion was monitored using an inertial measurement unit (IMU) also developed in our laboratory [22]. The IMU captured 3–axis each of accelerometer, rate gyroscope, and magnetometer data. The complete experimental setup is shown in Figure 2.

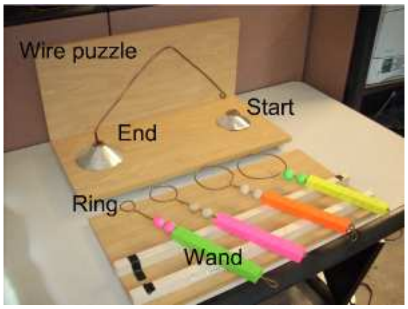

Fig. 3. The wire puzzle and wand setup. Wands of different difficulties are shown. Multiple puzzle shapes were also used. Participants guided the wand along the wire puzzle from Start to End, and back, attempting to avoid contact between the puzzle and the wand.

B. Software Framework

The software architecture of the SAR system was developed by Mead et al. [6] and consists of a task manager, a task–oriented controller, and activity layers. The *task manager* is the entry point and main system client; it manages the robot behavior at the beginning of each interaction and during transitions between tasks. The *task–oriented controller* guided the user during the actual performance of the practice task, kept track of the estimated user state, and determined the appropriate feedback regarding how many errors were made, or instructions for completing the puzzle. Finally, the *activity layers* provide system input and output. The *user* activity layer obtained input from the puzzle data (# of errors and movement time) and the IMU data. Robot verbal and non-verbal gestures, including providing encouragement, knowledge of performance, pointing at wands, and nodding, were controlled by the *robot* activity layer. These components were used together to create a dynamic, adaptive interaction.

IV. Methods

For our study, the autonomous humanoid SAR robot Bandit initiated, motivated, and terminated the experimental interactions. The experimenter's only roles were the administration of consent forms, motor function assessments, and surveys. After administering assessments, the experimenter led the participants into the room with Bandit; after placing the IMU on the participant's wrist, the experimenter left the room and allowed Bandit to run the remainder of the experiment. At the completion of the 3 15–minute practice sessions, the experimenter returned to the room, removed the IMU, administered the exit survey, and ended the session. We recruited 5 participants for the study. The cohort consisted of 3 males and 2 females between the ages of 24 and 75. All were individuals in the chronic phase of stroke recovery, right–hand dominant and right–hand affected by stroke, with UE Fugl–Meyer Assessment (FMA) scores between 31 and 60 (with 66 being the maximum possible score).

The practice schedule took place over 3 days with breaks of 1–2 days between each session. On Day 1, motor assessments were administered by a physical therapist. Subsequent to this, participants practiced the task for 3 15–minute sessions, with 10–minute breaks in between. Each session consisted of many bouts, where a bout is defined as completing the puzzle once, from Start to End and back. The number of bouts in each session depended entirely on the participant's speed of motion. On Days 2 and 3, no motor assessments were administered; the time was spent in the 3 15–minute sessions and breaks in between. A different wire puzzle was used for each day, increasing in difficulty on each day. The puzzle used on Day 3 was the longest and had the most curves/bends, thereby requiring the most pronation/supination at the wrist.

The robot provided instruction, feedback, and motivation. The instruction was provided at the beginning of each session, the beginning of each bout, and when users made errors. At the beginning of each session, the robot described the rules and goals of the wire puzzle task. At the beginning of each bout, the robot told the user which wand to use, and pointed to the wand with its right hand. Whenever the user made an error, such as using the wrong wand or failing to moving the wand in the right direction, the robot reiterated the task instructions.

Feedback was provided at the end of each bout. The robot provided knowledge of performance in the form of movement time and the number of errors. For example, it said: "You took five seconds, and touched the wire four times." In addition to verbalizing performance results, the robot nodded its head with an amplitude proportional to the user's performance.

Motivation was provided in the form of verbalized encouraging statements (e.g., "good job", "congratulations"). Further, the robot made congratulatory gestures (e.g., moving its arms up and down in a cheering motion) in response to improved performance.

In addition to the measures described in the previous section (puzzle and IMU data), we also collected fatigue and psychometric data. We collected self–reported fatigue measures at the start and end of each 15–minute session, and survey data regarding the quality and quantity of the robot gestures and verbalizations at the end of each day. We also obtained data regarding the perceived usefulness of the task with a survey based on the valid and reliable Intrinsic Motivation Index scale [23].

V. Data Analysis and Results

Motion smoothness was used as a performance metric for the participants. This feature has been used as a measure of motion quality in the domain of motor control [24] [25]. Human motion can be broadly categorized into *voluntary* and *involuntary* components. Voluntary motion is intentional and is characterized by the frequency band between 0.1 and 2Hz. Involuntary motion includes jerk and tremor, best captured by the higher band, between 4 and 8Hz.

We analyzed accelerometry data for the 5 participants over the 3–day experiment. The data were preprocessed using a fifth order Butterworth low pass filter (15Hz cutoff frequency), to remove high frequency noise, and a high pass filter (0.1Hz cutoff frequency), to remove low frequency

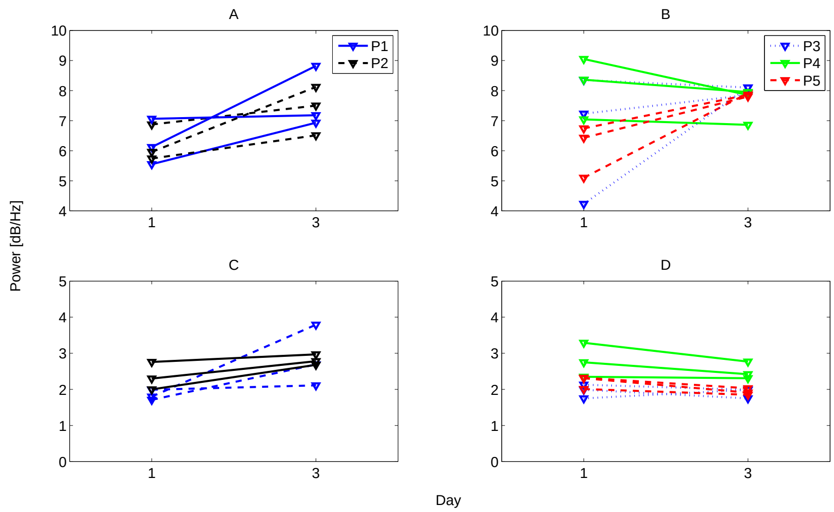

Fig. 4. Individual power spectrum data for all participants. Plots A and C depict the results for the moderate severity group in the 0.1–2Hz and 4–8Hz frequency bands, respectively. Plots B and D depict the results for the mild severity group in the 0.1–2Hz and 4–8Hz frequency bands, respectively.

device drift components. Next, the power (in dB/Hz) was computed using the formula in Equation 1:

$$\text{Power} = \frac{\sum (F_{ix}^2 + F_{iy}^2 + F_{iz}^2)}{N} \quad (1)$$

where F_i are the Fast Fourier Transform (FFT) coefficients for the $x-$, $y-$, and $z-$axis accelerometer signals, and N is the number of FFT coefficients in a given frequency band. This computation was performed for the 0.1–2Hz low frequency band, B_{lf} and the 4–8Hz high frequency band, B_{hf} for each 15–minute practice session, and for each participant. After consultation with a physical therapist, we divided our participants into two groups: the two participants in our *moderate severity* MoS group had UE FMA scores of 37 and 37 while the three participants in the *mild severity* (MiS) group had UE FMA scores of 46, 51, and 51. The idea behind this segregation was to study the effect of SAR–based intense motor task practice on the motor functionality of participants with mild and moderate severity. It is known that, according to the challenge point framework (CPF), participant skill level interacts with functional task difficulty and task performance [26]. We began by analyzing the power values for each participant individually between Days 1 and 3. We used Days 1 and 3 to obtain a comparison between performance with and without task familiarity. This is not a learning study that focuses on the participants learning a specific task over multiple sessions. Instead, the participants performed different and increasingly more difficult wire puzzle tasks within each session and on each day. Performance on Day 1 reflects ability with minimal task familiarity, and can be considered their baseline performance. Performance on Day 3 reflects abilities after having gained familiarity with the task. In future studies, pre-/post–assessment measures of functional ability will be used to establish a functional baseline and outcome change for participants. Figure 4 depicts the values for the low and high frequency band groups, B_{lf} and B_{hf}, and the MoS and MiS groups. Note that individual data are displayed; the MoS group consisted of participants 1 and 2 ($p1$, $p2$) and the MiS group consisted of participants 3, 4, and 5 ($p3$, $p4$, $p5$). The $y-$axis is power in [db/Hz], and the $x-$axis is the intervention day. Each line represents the change for a given 15–minute session. In Figure 4A, $p1$ has 3 lines representing power change between Day 1, first 15–minute block and Day 3, first 15–minute block; Day 1, second 15–minute block and Day 3, second 15–minute block; and Day 1, third 15–minute block and Day 3, third 15–minute block.

When evaluating the voluntary motion band (0.1–2Hz), we note that in the MoS group (Figure 4A), the amount of power increases for all participants. With the MiS group (Figure 4B), the results are mixed, with some instances of power increase, and some of decrease. When looking at the jerk band (4–8Hz), in the MoS group (Figure 4C), once again, the amount of power increases (indicating motion is getting less smooth). However, for the MiS group (Figure 4D), the amount of power in this band decreases in all but one case. This is indicative of the fact that motion for the MiS group got smoother over the course of the 3 days.

To evaluate the relationships between these data, we performed a repeated measures analysis of variance (ANOVA) within the MoS and MiS groups. We first performed the analysis for all data points, without regard for the frequency bands. The results, shown in Table I, indicate significant correlation. This would indicate that individuals in each group had virtually identical performance on the task; however, observations of video recordings of the practice sessions indicated that some variability did exist. This led us to investigate the correlation for each group *within* the frequency bands we have described. The results of this analysis are depicted in Table II. The results only indicate significant

TABLE I
ANOVA RESULTS FOR MILD AND MODERATE SEVERITY CORRELATION

	Correlation Coefficient
p1×p2	0.9579
p3×p4	0.8976
p3×p5	0.9420
p4×p5	0.9479

TABLE II
ANOVA RESULTS FOR MILD AND MODERATE SEVERITY CORRELATION, WITHIN FREQUENCY BANDS

	Frequency band	Correlation Coefficient
p1×p2	B_{lf}	0.6088
p1×p2	B_{hf}	0.5779
p3×p4	B_{lf}	-0.0435
p3×p5	B_{lf}	0.5552
p4×p5	B_{lf}	0.1299
p3×p4	B_{hf}	0.1735
p3×p5	B_{hf}	0.0454
p4×p5	B_{hf}	0.7446

correlation in one instance (p4×p5). We discuss this result in Section VI. We also wanted to investigate any group effects. To do so, we computed the mean and variance of power in the various bands for all members of each group (MoS and MiS). Figure 5 depicts the changes in power in B_{lf} over the course of the 3 days for both groups. Figure 6 depicts the changes in power in B_{hf} over the course of the 3 days. Visually, it appears that there are similar trends for both groups in the 0.1–2Hz band, and an inverse relationship in the 4–8Hz band. To evaluate this relationship, we performed a repeated measures ANOVA on the mean values between both groups. The results are shown in Table III, and indicate non–significant positive correlation in B_{lf}, and non–significant negative correlation in B_{hf}.

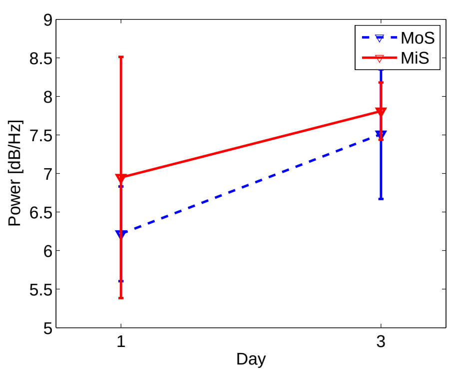

Fig. 5. Power in the 0.1–2Hz frequency band for mild and moderate severity individuals over the 3 day practice period.

TABLE III
ANOVA RESULTS COMPARING MEAN VALUES BETWEEN MILD AND MODERATE SEVERITY GROUPS

	Frequency band	p-value
MoS×MiS	B_{lf}	0.207
MoS×MiS	B_{hf}	-0.432

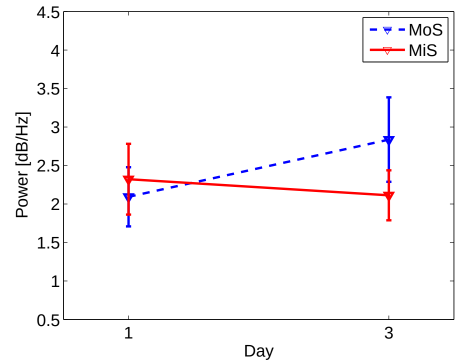

Fig. 6. Power in the 4–8Hz frequency band for mild and moderate severity individuals over the 3 day practice period.

VI. DISCUSSION

A. Changes in Voluntary Motion

The results depicted in Figures 5 and 6 indicate that, for the MiS and MoS groups, the mean amount of power in the voluntary motion band increased between days 1 and 3. If we look at the individual data depicted in Figure 4, we see that power in this band increased for all participants in the MoS group, and only some of the MiS group. As indicated in the literature, skill acquisition (or motor learning) has been correlated with increased power in this frequency band. For those who showed decreased power in this band, there was no skill acquisition; this indicates that the participants were operating above or below the optimal challenge point, and that no learning occurred.

The trend visible in Figure 5 indicates that a similar mechanism may be at work in both the MoS and MiS groups. For both groups, there is a net increase in power in this band. The lack of significant correlation between the means of the two groups is likely due to the small sample size; we anticipate that with additional data, we will be able to further validate this hypothesis.

B. Changes in Jerk/Involuntary Motion

As depicted in Figure 6, the MiS group showed decreased power in the jerk frequency band. The MoS group, however, showed increase in the amount of power in this band. There was negative correlation between the groups (though not statistically significant). This is likely due to the relative level of task difficulty for the MoS group. The power values in this band indicate that participants' motion was not getting smoother, and thus, there was no apparent motor learning taking place in the MoS group.

Looking again at the individual performances in Figure 4D, we can see that, for the MiS group, all instances excluding one indicated a decrease in power. This is most compelling: these results show that MiS individuals obtained useful practice, indicated by improved motion quality (smoothness). This could also indicate that MoS individuals were unable to cope with the difficulty level, and motion quality decreased over time.

C. Automated Robot–Guided Intervention

We reiterate here that the intervention was administered completely autonomously by the SAR robot, based on observations of the user state obtained from the various sensor modalities. This study thus shows that our SAR system can be used to affect desirable behavior changes in some individuals post–stroke, but studies with larger sample sizes are needed to determine if the results are statistically significant. To properly adapt the system, data from this study can be used to characterize a range of UE FMA scores for which the task, as designed, is appropriate. While this will be beneficial to the population, it will also allow us to gain more insight into the human–robot interaction, as the task will be more directly matched to the participants' challenge level. Evidence has shown that maintaining an appropriate challenge level in human–human interactions has a number of benefits, both physical and psychological [26]. If we can more adequately maintain challenge level, we can take advantage of these benefits to strengthen SAR-guided interaction.

VII. Conclusions

We have presented a socially assistive robot–guided interaction for motor task practice. The initial results from this work have shown that this interaction, administered completely autonomously by the robot, effected motor changes in the target population. Further validation is required to determine if the outcomes have clinical significance, but we believe that this adds support to the demonstrated potential for the continued investigation of the use of SAR methods in the administration of intense motor task practice. Future work includes gesture assessment using metrics for trajectory precision, velocity, and motion smoothness.

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References

[1] D. J. Feil-Seifer and M. J. Matarić, "Defining socially assistive robotics," in *International Conference on Rehabilitation Robotics*, Chicago, IL, Jun 2005, pp. 465–468.

[2] K. D. T. Fong, I. Nourbakhsh, "A survey of socially interactive robots," *Robotics and Autonomous Systems, Special issue on Socially Interactive Robots*, vol. 42, no. 3-4, pp. 143–166, 2003.

[3] T. Shibata and K. Wada, "Robot therapy - a new approach for mental healthcare of the elderly." *Gerentology*, Jul 2010.

[4] K. Dautenhahn, C. L. Nehaniv, M. L. Walters, B. Robins, H. Kose-Bagci, N. A. Mirza, and M. Blow, "Kaspar - a minimally expressive humanoid robot for human-robot interaction research," *Applied Bionics and Biomechanics*, vol. 6, no. 3, pp. 369–397, 2009.

[5] W. H. Organization, "Burden of disease statistics," 2010, http://www.who.org.

[6] R. Mead, E. Wade, P. Johnson, A. B. S. Clair, S. Chen, and M. J. Matarić, "An architecture for rehabilitation task practice in socially assistive human-robot interaction," in *19th IEEE International Symposium in Robot and Human Interactive Communication*, Viareggio, Italy, Sep 2010.

[7] M. J. Matarić, A. Tapus, C. J. Winstein, and J. Eriksson, "Socially assistive robotics for stroke and mild TBI rehabilitation," in *Advanced Technologies in Rehabilitation*. IOS Press, 2009, vol. 145, pp. 249–262.

[8] R. Elble and W. Koller, *Tremor*. Baltimore: Johns Hopkins, 1990.

[9] J. Desrosiers, R. Hbert, G. Bravo, and lisabeth Dutil, "Upper extremity performance test for the elderly (tempa): Normative data and correlates with sensorimotor parameters," *Archives of Physical Medicine and Rehabilitation*, vol. 76, no. 12, pp. 1125 – 1129, 1995.

[10] S. Wolf, P. Catlin, M. Ellis, A. Archer, B. Morgan, and A. Piacentino, "Assessing wolf motor function test as outcome measure for research in patients after stroke." *Stroke*, vol. 32, no. 7, pp. 1635–1639, July 2001.

[11] A. A. Duschau-Wicke, T. Brunsch, L. Lunenburger, and R. Riener, "Adaptive support for patient-cooperative gait rehabilitation with the lokomat," *IROS*, pp. 2357–2361, 2008.

[12] S. Banala, S. Kim, S. Agrawal, and J. Scholz, "Robot assisted gait training with active leg exoskeleton (alex)." *IEEE Trans Neural Syst Rehabil Eng.*, vol. 17, no. 1, pp. 2–8, Feb. 2009.

[13] D. Reinkensmeyer, L. Kahn, M. Averbuch, A. McKenna-Cole, B. S. B, and W. Rymer, "Understanding and treating arm movement impairment after chronic brain injury: progress with the arm guide." *J Rehabil Res Dev.*, vol. 37, no. 6, pp. 653–662, Nov–Dec 2000.

[14] T. Nef, M. Guidali, and R. Riener, "ARMin III - arm therapy exoskeleton with ergonomic shoulder actuation," *Applied Journal of Bionics and Biomechanics*, vol. 6, no. 2, pp. 127–142, 2009.

[15] Y. Choi, J. Gordon, D. Kim, and N. Schweighofer, "An adaptive automated robotic task-practice system for rehabilitation of arm functions after stroke," *IEEE Transactions on Robotics*, vol. 25, no. 3, pp. 556–568, June 2009.

[16] A. C. Lo, P. D. Guarino, L. G. Richards, J. K. Haselkorn, G. F. Wittenberg, D. G. Federman, R. J. Ringer, T. H. Wagner, H. I. Krebs, B. T. Volpe, C. T. Bever, D. M. Bravata, P. W. Duncan, B. H. Corn, A. D. Maffucci, S. E. Nadeau, S. S. Conroy, J. M. Powell, G. D. Huang, and P. Peduzzi, "Robot-assisted therapy for long-term upper-limb impairment after stroke." *N Engl J Med.*, vol. 326, no. 19, pp. 1772–1783, May 2010.

[17] J. Fasola and M. J. Matarić, "Robot motivator: Improving user performance on a physical/mental task," in *Proceedings of the International Conference on Human-Robot Interaction*, Mar 2009.

[18] A. Tapus, C. Tapus, and M. J. Matarić, "The use of socially assistive robots in the design of intelligent cognitive therapies for people with dementia," in *International Conference on Rehabilitation Robotics*, Jul 2009.

[19] D. J. Feil-Seifer, M. P. Black, M. J. Matarić, and S. Narayanan, "Toward designing interactive technologies for supporting research in autism spectrum disorders," in *International Meeting for Autism Research*, Chicago, Il, May 2009.

[20] E. Wade, A. Parnandi, and M. J. Matarić, "Automated administration of the wolf motor function test for post-stroke assessment," in *ICST 4th International ICST Conference on Pervasive Computing Technologies for Healthcare 2010*, 2010.

[21] A. Parnandi, E. Wade, and M. J. Matarić, "Motor function assessment using wearable inertial sensor," in *32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'10)*, 2010.

[22] E. Wade and M. J. Matarić, "Design and testing of lightweight inexpensive motion-capture devices with application to clinical gait analysis," in *Proceedings of the International Conference on Pervasive Computing*, Aug 2009, pp. 1 – 7.

[23] "Intrinsic motivation inventory," 2010, http://www.psych.rochester.edu/SDT/measures/IMIdescription.php.

[24] J. Bernhardt, P. Bate, and T. Matyas, "Accuracy of observational kinematic assessment of upper-limb movements." *Phys Ther.*, vol. 78, no. 3, pp. 259–270, Mar. 1998.

[25] P. O'Suilleabhain and J. Matsumoto, "Time-frequency analysis of tremors." vol. 121, no. 11, pp. 2127–2134, 1998.

[26] M. Guadagnoli and T. Lee, "Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning." *J. Mot. Behav.*, vol. 36, no. 2, pp. 212–224, 2004.