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Work with me, not for me: Relationship between robotic assistance and performance in subacute and chronic stroke patients

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Abstract

Introduction: Studies in robotic therapy which applied the performance enhancement approach report improvements in motor performance during training, though these improvements do not always transfer to motor learning.

Objectives: We postulate that there exists an assistance threshold for which performance saturates. Above this threshold, the robot's input outweighs the patient's input and likely learning is not fostered. This study investigated the relationship between assistance and performance changes in stroke patients to find the assistance threshold for performance saturation.

Methods: Twelve subacute and chronic stroke patients engaged in five sessions (over two weeks, each 60 min) in which they performed a reaching task with the rehabilitation robot H-Man in presence of varying levels of haptic assistance (50 N/m to 290 N/m, randomized order). In two additional sessions, a therapist manually tuned the assistance to promote maximal motor learning.

Results: Higher levels of assistance resulted in smoother and faster performance that saturated at assistance levels with $K \geq 110$ N/m. Also, the therapist selected assistance levels of $K = 175$ N/m or below.

Conclusion: The findings of the study indicate that low levels of assistance ($K \leq 175$ N/m) can sufficiently induce a significant change in performance.

Keywords

Assistive technology, decentralized care, neurorehabilitation, robotic rehabilitation, robotic assistance, stroke rehabilitation

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Introduction

The world's population is aging, with the number of people aged 65 years or older expected to reach 1.6 billion (17% of the global total) by 2050.[1] The risk of stroke increases with age,[2] with incidences doubling each decade after the age of 55.[3,4] Healthy older adults and those affected by stroke often suffer from deficits in upper extremity sensorimotor dysfunction due to changes in both the central and peripheral nervous systems.[5] Results from studies exploring the time course of recovery report that approximately up to 70% of the patients have residual impairment in the upper extremity six months post stroke.[6–9] The prevalence of motor dysfunction in elderly and stroke populations has motivated research groups to develop technology-assisted systems that can decrease the workload of clinicians, while also facilitating motor re-learning. In the last few decades, multiple robotic solutions have been developed that promote sensorimotor learning in populations with sensorimotor impairments such as stroke.[10–12] Overall, results of clinical studies have demonstrated that robot-assisted training is at least as effective as conventional physical therapy.[13–17]

In addition to considerations regarding the mechanical design of the robotic systems, there has been ample interest in elucidating robotic interactive control algorithms that can positively influence *motor learning* (i.e. the processes associated with practice or experience that leads to long-term changes in the ability to perform a skill[18]). In a very common training scheme (known as the 'performance enhancement approach'), the movements of a patient are haptically guided or constrained in some fashion,[19–21] with the goal of enhancing the patient's *motor performance* (i.e. an observable and measurable change in motor skill during training[22]) during the task. The assistance provided by the rehabilitation robot enables patients to perform otherwise inexecutable movements, which is said to stimulate brain plasticity and sensorimotor learning processes.[23,24] Prior research has demonstrated that robotic assistance improves task performance during training,[20,21] but these effects are often short-lived and do not translate to long-term learning.[21] For example, Liu et al.[21] conducted a study in which healthy subjects were first guided in a tracing task (i.e. training phase) in such a way that the subjects were not required to actively support the movement. Then, when the subjects were asked to replicate the movement without any assistance (i.e. recall phase) from the robot immediately afterwards, the subjects made large tracing errors. This finding is congruent with the 'guidance hypothesis',[25] which argues that when guidance is provided very frequently during new skill acquisition, the user relies on said guidance to perform the task and/or learns an altered task, and when the feedback is absent, there is a noticeable decline in performance quality.[26,27] Thus, for the case of robotic rehabilitation, haptic guidance may result in suboptimal motor learning if too much support or assistance is provided during training.[21,26] In addition, too much assistance may motivate slacking in the user[28,29] since the user can rely on the robot completing the task, but effort is considered crucial for motor learning.[30–32]

Taken together, there is strong evidence that performance and learning are not directly related[33]: a proficient motor performance during training (in presence of assistance) does not necessarily result in a proficient motor performance when assistance is removed (i.e. learning). We agree that robotic assistance influences motor performance (metrics sensitive to the motor condition, as e.g. smoothness), but argue that there exists an assistance threshold for performance saturation (for a given robotic device) for which assistance levels higher than such a threshold do not result in further performance improvements. Likely, in these cases, the robot does most of the task and this, in consequence, results in a slacking response by the user. Concluding from the precedent on the relationship between motor performance and motor learning, assistance above that threshold does, therefore, not provoke any further learning gain. To the best of our knowledge, this threshold has not been systematically determined yet for stroke patients with upper limb dysfunction.

Knowledge about the maximal assistance requirements would directly translate to the power requirements of a rehabilitation device. Early upper limb robotic systems were designed to fully support a patient's movements (e.g. MIT-Manus,[34] ARMin,[35] HapticMaster[36]), which resulted in complex, high-powered setups. The high cost and safety issues of these complex rehabilitation robotics restrict their use to centralized care facilities (e.g. hospitals), and thus limit their application to decentralized environments (i.e. community centers or patient's home).[37] Fortunately, there is growing interest in designing lower powered neurorehabilitation robots that can be used in decentralized locations[38,39] (e.g. hCAAR,[38] H-Man[40]), which in contrast to early systems are likely to be more accessible for patients due to their reduced costs and inherent safety. Knowing the maximal range of assistance required for performance saturation, and, hence, the maximal required power supply is a crucial step for the future development of devices aiming to provide therapy in decentralized settings while avoiding unnecessary power disposability.

As such, the aim of the present study was to find this assistance threshold by investigating the relationship between five different robotic assistance levels and motor performance in presence of assistance in 12 subacute and chronic stroke patients. To achieve this aim, we utilized a two degrees of freedom robotic manipulator (hereafter referred to as 'H-Man') designed for upper limb assessment and rehabilitation training.[40] Stroke patients performed an upper extremity reaching task in five sessions (each 60 min) over a period of two weeks, under varying levels of robotic assistance (i.e. 50, 110, 170, 230, and 290 N/m). Differences in standard kinematic performance metrics (i.e. spectral arc length (SAL) and normalized total time (T_{norm})) were examined. A secondary aim of this study was to gain an understanding of optimal robotic assistance for motor learning from the rehabilitation therapist' viewpoint. Thus, after the two-week rehabilitation program, patients completed another two sessions with the H-Man robot (each 60 min), during which the rehabilitation therapist tuned the assistance levels to induce a maximum learning effect based on motor behavioral characteristics of the participant. These results are the first step in elucidating an optimal assistance threshold for the H-Man, with the aim to develop guidelines for future developments of rehabilitative devices employed in decentralized care settings.

Methods

Participants

Twelve subacute and chronic stroke patients (age: 55.8 ± 10.0 years, 7 males, time since stroke: 11.3 ± 6.5 months) participated in the present study (Table 1). Study inclusion criteria were first-ever clinical stroke (ischaemic or haemorrhagic) confirmed by brain imaging, post-stroke duration of 3 to 24 months, with shoulder abduction and elbow flexion greater or equal to 3/5 on the Medical Research Council scale for muscle strength, and a Fugl–Meyer Upper Extremity Motor Assessment (FMA)[41] score of 20–50 or predominant motor ataxia or incoordination (FMA > 50). Participants were excluded if they had any non-stroke related arm impairment, moderate arm spasticity as indicated by the Modified Ashworth Scale[42] (MAS > 2), moderate shoulder pain (VAS > 5/10), visual impairment (hemianopia), visual-spatial neglect, and/or cognitive impairments (Mini Mental State Exam (MMSE)[43] < 26/30).

Prior to subject recruitment, ethical approval was obtained from the Domain Specific Institutional Review Board (IRB) of the National Healthcare Group (NHG), Singapore. All subjects gave written informed consent prior to screening procedures and recruitment (clinical-trial ID: NCT02188628 – clinicaltrials.gov). Also, written informed consent was provided by all patients for patient information to be published. The study was conducted in accordance with the declaration of Helsinki.

Apparatus and protocol

The experimental apparatus used for the study is the rehabilitation robot H-Man[40] (Figure 1): a compact planar, upper extremity robot designed for the use in rehabilitation settings and for human motor control experiments in stroke and neurologically healthy participants.[44,45] The participant was seated in a

Table 1. Stroke patient characteristics.

Age (years)	Gender	Time since stroke (months)	Stroke type	Affected arm	FMA (0–66)
FMA ≥40					
66	M	6	Ischaemic	R	64[a]
54	M	22	Ischaemic	R	55[a]
75	M	4	Ischaemic	L	48
57	F	7	Ischaemic	R	46
45	M	13	Haemorrhagic	L	45
52	F	5	Haemorrhagic	L	43
56	F	11	Haemorrhagic	R	43
57.9 ± 9.8	*4M, 3F*	*9.7 ± 6.3*	*4I, 3H*	*3L, 4R*	*49.1 ± 7.7*
FMA < 40					
52	M	20	Haemorrhagic	R	30
51	F	7	Haemorrhagic	R	29
38	F	16	Ischaemic	R	29
57	M	6	Ischaemic	R	28
67	M	19	Ischaemic	L	20
53.0 ± 10.5	*3M, 2F*	*13.6 ± 6.7*	*2H, 3I*	*1L, 4R*	*27.2 ± 4.1*

[a]Indicates pre-dominant motor ataxia.
Note. Italics represent the averages of the above lines.

Figure 1. A participant using the current version of H-Man. The visual interface illustrates the reaching task by providing visual cues for the start position ('Start'), the current position ('Cursor') and the target position ('Target').

height-adjustable chair in front of H-Man that was placed on a fixed table, such that the center of the sternum was aligned with the handle of the H-Man robot and the elbow bent at 90°. A display was used to provide visual feedback and the representation of the task. The visual stimuli consisted of the start and target positions, the cursor position and task instructions. The participant's trunk was physically restrained to limit trunk movements during the task. At the start of each trial, a target was visually displayed on the computer monitor in one of the contralateral, ipsilateral and sagittal plane directions (angles of −45°, 0°, and +45° from the vertical axis, respectively) at a distance of 16 cm to the initial position. The participant grasped the robot's handle (if needed a wrist strap was provided) and moved the cursor from the start position to the target (point-to-point reaching task).

During the point-to-point reaching task, assistance was provided via a target attraction impedance controller[46,47] by the equation:

$$F = K(x - x_{target}) + B\dot{x}$$

where K is the stiffness, B the damping, x the present position (user-controlled cursor) and x_{target} the final position. The assistance was rendered as a pulling force between the user-controlled cursor position and the target position (virtual spring-damper system). The protocol was carried out in five training sessions, each of 60 min, over a period of two weeks with supervision from one occupational therapist and engineers. In each of the five sessions, the point-to-point reaching task was performed with a different, but fixed, level of assistance, i.e. different levels of stiffness K (50, 110, 170, 230, and 290 N/m). The order of the assistance levels was randomized for each participant.

After the two-week program, patients performed two additional sessions (each 60 min), during which one rehabilitation therapist (the same therapist for all subjects who had many years of experience of occupational and robotic therapy with stroke patients) was asked to tune the assistance levels to induce a maximum learning effect for the respective participant. Starting from a medium level of assistance for each patient, the therapist could adjust (increasing or decreasing) the assistance level at any time while observing the patient's movements, if considered useful for learning.

Data and statistical analysis

Participants were divided into two impairment groups based on the FMA score before the commencement of the intervention[17]: Five patients were assigned to the moderately to highly impaired (FMA <40) group and seven to the mildly impaired group (FMA ≥ 40).

For the first part of the study, in which assistance levels were systematically varied, the raw kinematic data (position and velocity) were filtered using a low pass filter (Butterworth: 6th order, cut-off frequency Fc: 20 Hz, sampling rate Fs: 1000 Hz). The filtered data were used in offline data processing to calculate the task performance indices adopted from the literature.[48] For each level of assistance, the data across the three directions were considered as tasks on a planar workspace and hence were combined in the analysis. Task performance in presence of the different levels of assistance was evaluated based on metrics that are considered sensitive to the motor condition and thus are of importance for movement evaluation.[49,50] As such, a smoothness metric spectral arc length (SAL)[51] and a temporal performance metric normalized total time (T_{norm}) were chosen. The smoothness metric SAL is a dimensionless measure of the length of the frequency spectrum curve of a speed profile over the bandwidth appropriate for the action. Movement smoothness is considered as an important indicator for motor re-learning in stroke patients, allowing for the quantification of sub-movements and thus of movement efficiency. There is ample evidence that reaching movements get smoother with motor learning[52] and post-stroke motor recovery.[50] T_{norm} is a measure of the temporal performance of each trial defined as the total time needed for the completion of a trial divided by the maximum distance covered in the respective trial. Temporal performance serves as an indicator for paresis[53] and somatosensory loss,[54] and is expected to improve with recovery.[49]

Differences in task performance metrics due to the different assistance levels and impairment groups were evaluated using a two-way analysis of variance (ANOVA) with group as the between-subject factor and assistance level as the within-subject factor.

Significant main effects and interactions were compared using Tukey's honest significant difference test (HSD).

For the analysis of the therapist's tuning of the robotic assistance, we analyzed the final assistance level that the therapist considered optimal for maximal learning for the respective patient.

Results

Task performance

Spectral arc length (SAL) values as a function of assistance level and group are shown in Figure 2. Smoother movements were observed for higher levels of assistance, $F(4,50) = 8.60$, $p < 0.001$. The change in smoothness appeared to reach a plateau with an increase in the level of assistance. This was verified by Tukey's HSD test that indicated that movements were smoother for the lowest assistance level (SAL(level 1) $= -2.72 \pm 0.41$) compared to all other assistance levels (SAL (level 2) $= -2.45 \pm 0.30$, $p_{\text{Level1-2}} < 0.05$; SAL(level 3) $= -2.31 \pm 0.18$, $p_{\text{Level1-3}} < 0.001$; SAL(level 4) $= -2.31 \pm 0.14$, $p_{\text{Level1-4}} < 0.001$; SAL(level 5) $= -2.22 \pm 0.12$, $p_{\text{Level1-5}} < 0.001$). Differences in SAL between all other levels did not reach significance (all p's > 0.05). In terms of inter-group performance variations, movements performed by the mildly impaired group were smoother than those performed by the highly impaired group (SAL(FMA ≥ 40) $= -2.34 \pm 0.26$ and SAL(FMA < 40) $= -2.48 \pm 0.35$), $F(1,50) = 4.88$, $p < 0.05$. The interaction between the level of assistance and impairment group was found non-significant, $F(4,50) = 1.20$, $p = 0.322$.

Normalized total time (T_{norm}) values dependent on assistance level and group are shown in Figure 3. In general, movements were completed in a shorter time period as assistance level increased, $F(4,50) = 6.46$, $p < 0.001$. As for the smoothness performance, post hoc analysis showed that performance in terms of T_{norm} was significantly worse for the lowest assistance level (T_{norm}(level 1) $= 14.32 \pm 7.64$ s/m) than for all other levels (T_{norm}(level 2) $= 10.76 \pm 4.26$ s/m, $p_{\text{Level1-2}} < 0.05$; T_{norm}(level 3) $= 9.93 \pm 4.04$ s/m, $p_{\text{Level1-3}} < 0.05$; T_{norm}(level 4) $= 9.51 \pm 3.27$ s/m, $p_{\text{Level1-4}} < 0.05$; T_{norm}(level 5) $= 8.06 \pm 2.65$ s/m, $p_{\text{Level1-5}} < 0.001$). Differences in T_{norm} between all other levels were not found to be significant (all p's > 0.05). There was also a significant main effect of impairment group on T_{norm} ($F(1,50) = 42.12$, $p < 0.001$), such that the mildly impaired group exhibited shorter total movement times than the moderately to highly impaired group (T_{norm}(FMA ≥ 40) $= 8.07 \pm 3.10$ s/m and T_{norm}(FMA < 40) $= 13.95 \pm 5.20$ s/m). The interaction between the level of assistance and impairment group was non-significant, $F(4,50) = 2.39$, $p > 0.05$.

Therapist's tuning of robotic assistance

For most patients (91.7%, $n = 11$), the therapist tuned the final assistance levels to a level lower than or equal

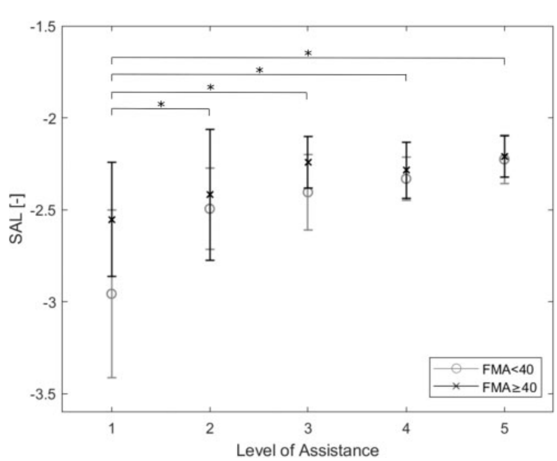

Figure 2. Smoothness performance (mean and standard deviation) in terms of spectral arc length (SAL) in presence of different levels of assistance of both impairment groups. Smoothness performance saturated from level 2 of assistance onwards (*indicates significance: $p < 0.05$).

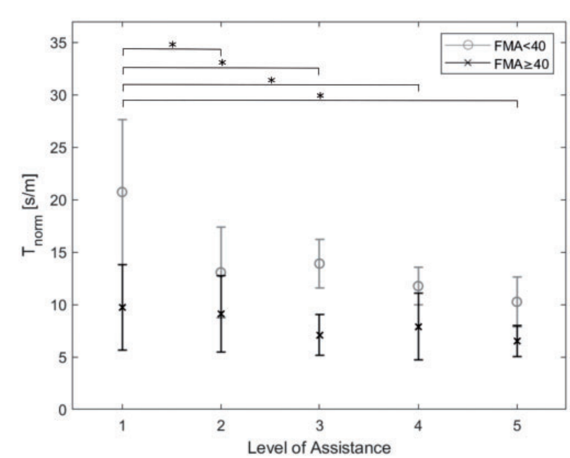

Figure 3. Performance (mean and standard deviation) in terms of total time normalized (T_{norm}) in presence of different assistance levels for both impairment groups. T_{norm} in the lowest level of assistance was significantly higher than in all other levels (levels 2–5), hence assistance levels higher than level 2 did not provoke further T_{norm} performance changes (*indicates significance: $p < 0.05$).

to 175 N/m. The only case in which the therapist adjusted the assistance to a level higher than 175 N/m was for the patient with the lowest FMA score (FMA = 20).

Discussion

This study investigated the relationship between robotic assistance and performance in 12 subacute and chronic stroke patients to find an assistance threshold after which no further performance gain can be achieved. Further, the study yielded an understanding of robotic assistance for motor learning from the rehabilitation therapist's viewpoint.

Overall, we observed a significant difference between groups for both performance metrics, whereby the mildly impaired stroke patients exhibited smoother movements and shorter movement times than the moderately to highly impaired patients. In addition, there was a trend toward smoother movements and shorter movement times as the level of robotic assistance increased. However, statistical analysis indicated that motor performance reached saturation at $K = 110$ N/m, after which higher levels of robotic assistance did not yield further improvements in either movement smoothness or movement times. The observation of this performance saturation indicates that when higher assistance levels are utilized in a robotic rehabilitation protocol for post-stroke upper limb dysfunction, the robot's input outweighs that of the patient (i.e. the robot is taking over most of the work required to complete the task). This, arguably, results in a reduction of overall effort by the user who allows the robotic device to move the upper limb to the target with minimal participation. Consequently, patients may modulate their force production based on the applied assistive force during task performance (i.e. slacking),[55,56] which ultimately reduces the possibility that robotic rehabilitation training would provoke somatosensory stimulation and initiate brain plasticity[23,24] and hence learning. This explanation is consistent with the work of Jarrassé et al.[57] in which the interaction between the patient and the rehabilitation robot is described akin to a teacher–student relationship. In this framework, the main purpose of the teacher (i.e. robot) is to assist the student (i.e. patient) in building his/her own capacity, rather than the robot exerting unidirectional control over the task performance (master-slave interaction). An assistance level above the threshold would arguably induce a master–slave interaction instead of the desired teacher–student relationship.

Moreover, results from the two manual tuning sessions indicated that the rehabilitation therapist selected values lower (or equal to) 175 N/m as the final assistance level for all but the most impaired stroke patient (i.e. FMA = 20). Although this value is higher than the assistance threshold obtained from the kinematic data, it is apparent from the viewpoint of a therapist with extensive robotic rehabilitation experience, that levels of assistance above 175 N/m are not required to induce optimal motor learning for a post- stroke population with FMA higher than 20. We do, however, acknowledge that the manual tuning data are preliminary, especially in light of the fact that we received input from a single rehabilitation clinician, and that we conducted only two manual tuning sessions. Nonetheless, clinicians are a critical partner in the delivery of decentralized rehabilitation, and our future work will investigate inter-therapist variations in manual tuning as a function of clinical experience and patient upper limb dysfunction.

Both parts of the study reveal that high assistance is not required for motor learning. Our study aimed to investigate a threshold for the performance enhancement approach. Combining the findings of both parts of the study, a stiffness threshold of 175 N/m seems appealing. As with any study, the present experiment comes with some limitations: First, while the results of our study suggest that high levels of robotic assistance do not improve motor performance, there is the possibility that the stiffness threshold may be different for robotic devices with dissimilar mechanical structures.

Moreover, the assistance levels used in the present study were based on the available power range of the H-Man device, and thus we cannot rule out the possibility that stiffness values greater than 270 N/m would not promote further motor performance. Second, the present study focused on motor performance and, therefore, we cannot directly translate our findings to motor learning since performance and learning are not necessarily related. Based on the current knowledge of motor learning, we assume that assistance levels higher than 175 N/m will not further foster learning. This hypothesis, however, needs to be confirmed in future work. Next, our findings cannot be generalized to the whole population of stroke patients given that the sample size was relatively small ($n = 12$) and patients with severe levels of upper limb weakness (i.e. FMA < 20) and comorbid difficulties were not eligible to participate. Given the heterogeneous nature of stroke characteristics and post-stroke upper limb impairments, future research will focus on a larger number of stroke patients across a broader neurological profile (e.g. FMA < 20) in order to fully evaluate the relationship between motor performance and robotic assistance.

Despite these limitations, the findings of our study have great implications for the design of future rehabilitation robotic systems aiming for decentralized care.

Lower powered devices may suffice in providing the required assistance for optimal motor learning. Although a quantifiable power safety limit for devices employed in decentralized settings cannot be provided yet, it is indisputable that the understanding that high assistance levels are unnecessary makes decentralized care more realizable.

Conclusion

This paper investigated motor performance variations (smoothness and movement time) in presence of different levels of haptic assistance with the upper limb rehabilitation robot H-Man. Results show a performance saturation for high levels of assistance ($K \geq 110\,\mathrm{N/m}$) as those assistance levels did not yield further performance improvements. We postulate that the performance saturation (level 2–5 [$K = 110$–$290\,\mathrm{N/m}$]) is a result of the robot taking over most of the work required to complete the task. Likely, this promotes slacking in the user and consequently, learning is not further promoted. The manual tuning behavior of the therapist points in the same direction since the final assistance level was set to maximal $K = 175\,\mathrm{N/m}$ for all but the most impaired patient. These findings are of great importance for the development of robots that target decentralized care: Lower assistance levels directly translate to the power requirements of a device.

Lower powered devices indisputably make decentralized care more realizable.

Authors' Note

Asif Hussain is also affiliated with ARTICARES Pte. Ltd.

Declaration of conflicting interests

AH and DC hold equity positions in ARTICARES Pte. Ltd, a company that manufactures this type of technology under license from Nanyang Technological University, Singapore.

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SK.

Contributorship

AH, AB, WD, CH, CK, LX, KC, DC conceptualized the study. KC, DC acquired the funding. LY, KC, DC administered the project. AH, AB, WD developed the software. VD, CK, CYN, LY, KC recruited the patients. AH, AB, WD, CH, VD, CK, CYN conducted the experiments. MA, KC, DC supervised the project. SK, AH, LX analyzed the data.

SK, AH, CH wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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