# An Investigation into the Reliability of Upper-limb Robotic Exoskeleton Measurements for Clinical Evaluation in Neurorehabilitation

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***Abstract*— Robotic exoskeletons are increasingly being used for neurorehabilitation, due to a number of perceived advantages. Once such advantage is the potential to use the large amounts of previously unavailable measurements to provide continuous assessment of the patient. This study investigates the validity of such measurements through an experimental protocol. Reaching movements within and outside an upper-arm rehabilitation exoskeleton (ArmeoPower) of 10 healthy subjects are compared using five commonly-used kinematic metrics (Peak Speed, Time to Peak Speed, Curvature, Smoothness, Accuracy). The study finds that (1) the robotic exoskeleton significantly affects the reaching movements of healthy subjects, (2) the measurements of the exoskeleton accurately represent the movements of the wrist, and (3) evolution of the in-exoskeleton movements over multiple sessions is indicative of changes in movements outside the robot, even though differences remain – suggesting that evolution of this data may be used to monitor patient progress.**

## I. INTRODUCTION

Robotic devices are increasingly being studied and used as tools for neurorehabilitation. The use of robotic devices for this purpose are thought to have a number of benefits, including the ability to conduct intensive sessions, controlled and repeatable motions, and the availability of measurements and data [1], [2].

The numerous sensors on robotic devices provide a multitude of information not previously available with traditional neurorehabilitation techniques. Information collected by these robotic devices can potentially be used to increase the frequency, accuracy and precision of clinical assessment and thus lead to a better understanding of the recovery process and customisation of the rehabilitation process.

Although several robotic devices already provide assessment facilities [3], care should be taken when such data is used in a clinical context. Indeed, the lack of mechanical transparency of the robotic systems may lead to undesired or uncontrolled effects of the system on patients' limbs while performing the assessment [4] and thus bias the measurements such that they no longer accurately reflect the true performance of the patient.

In the present study, we investigated how data from a robotic upper-limb exoskeleton (ArmeoPower from Hocoma, Switzerland) may be used for clinical evaluation through analysis of two objectives. First, we characterise the uncontrolled effects of this exoskeleton on the movements of healthy subjects. Secondly, we check the accuracy of the data itself, when compared to external sensors. This is achieved through the observation of classical movement metrics, based on ideal hand movements [5] during reaching tasks.

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This study finds that assessment using robotic rehabilitation devices should be approached with caution, as the metrics calculated on reaching movements attempted whilst 'In Robot' can be significantly different when compared with 'Free' movements, and as such, do not necessarily accurately represent the reaching capabilities of the patient. However, the data recorded by a robot can accurately represent the (affected) physical movement. Additionally, evolution of the movement 'In Robot' is indicative of changes in the movement in 'Free' space, indicating that such data may be suitable for use in inter-robot comparisons.

## II. METHODS

This study utilises partial results from an experiment comparing the reaching movements in two conditions – 'Free Reaching' and 'Robot Reaching' (see Fig. 1). Under the 'Free Reaching' condition, subjects wore only lightweight sensors, and thus it is assumed that the subjects' natural movements were not affected. In 'Robot Reaching', subjects perform the actions within the robotic exoskeleton set to 'transparent mode' – designed to compensate only for the robot's own friction, weight and mechanical properties. The study was approved by the University of Melbourne Engineering Ethics Advisory Group under the ethics identification number #1442734.

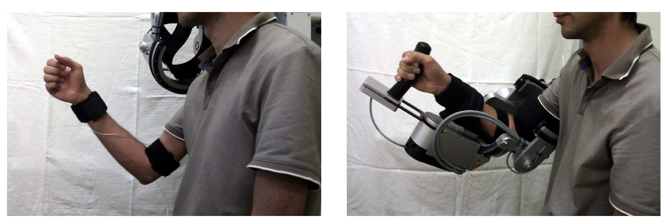

Fig. 1: Experimental Setup in 'Free Reaching' (left) and 'Robot Reaching' (right) conditions. Black straps shown in 'Free reaching' hold lightweight magnetic sensors.

### A. *Experimental Setup*

Ten naïve, healthy subjects (28.2 $\pm$ 6.1 years old), participated in the study. The full protocol included five sessions (see Fig. 2). The first session consisted of a 'Free Reaching' block followed by a 'Robot Reaching' block. The last session consisted of a 'Robot Reaching' block followed by a 'Free

Reaching' block. Intermediate sessions consisted of a 'Robot Reaching' block only. During each block, subjects completed the reaching task 120 times with their dominant hand (left dominant: $n = 1$, right dominant: $n = 9$). Only results from the first and last sessions are reported in this paper. The remaining sessions were included in the experiment for a future study analysing the learning trends in more detail.

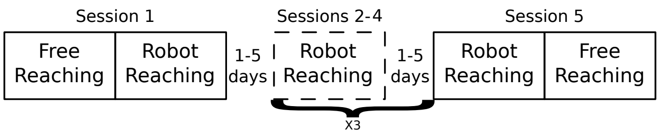


Fig. 2: Sessions and conditions order. Only results of session #1 (first) and #5 (last) are represented here.

*1) Data collection:* Measurements were made using the 3D Guidance trakSTAR system (Ascension Technology Corporation, USA) providing 6-dof position and orientation measurements at three magnetic sensors, placed on the shoulder, the end of the *humerus*, and the wrist, recording at approximately 30Hz. In 'Robot Reaching' trials, data from the exoskeleton was also recorded. This data included the calculated position of the wrist recorded at approximately 60Hz. In trials where both sets of data were available, the two datasets were synchronized in post-processing.

*2) Reaching Task:* A 3D virtual environment (see Fig.3) was presented to the subject, in which the position of the cursor was mapped to the position of the magnetic sensor on the wrist. Subjects were asked to move from a home position to a target and stop within one second. Commencement of the movement was to be when an audible tone was played through the computer's speakers. A countdown was also presented visually on the screen. On completion of a successful movement – one in which the subject had reached the target, and stayed within the target for 0.4s – an affirmative tone was played and a score was incremented. If the movement was not successful – the subject had either not reached the target position within 1s, or had reached it and moved away from it – a different tone was played and the score not incremented.

Within the virtual environment, the $x$-axis corresponded to left/right, $y$ to down/up, and $z$ to backwards/forwards. The axes were scaled with respect to the distance between the shoulder and humerus sensor at an initial calibration stage, such that all targets were reachable from within the robot.

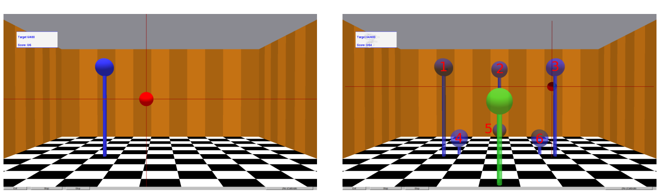

Fig. 3: Virtual environment. Left: target one (blue) and cursor (red). Right: the six different targets (blue), home position target (green) and cursor (red).

A total of six different targets were used (listed in Table I and seen in Fig. 3). The home position was located in the coronal plane aligned with the shoulder of the reaching arm, at a position requiring approximately 45° shoulder flexion, and 90° elbow flexion. All movements required forward motion, to the up-left, directly up, up-right, down-left, directly down and down-right from the home position. The locations of these targets were chosen such that they were of significant distance from the home position and reachable when the subject was in the exoskeleton.

TABLE I
TARGET POSITION (VIRTUAL COORDINATES)

| Target | $x$ | $y$ | $z$ | Target | $x$ | $y$ | $z$ |
|---|---|---|---|---|---|---|---|
| Home | 0.5 | 0.5 | 0.0 | - | - | - | - |
| 1 | 0.3 | 0.8 | 0.45 | 4 | 0.35 | 0.15 | 0.5 |
| 2 | 0.5 | 0.8 | 0.55 | 5 | 0.5 | 0.15 | 0.85 |
| 3 | 0.7 | 0.8 | 0.45 | 6 | 0.65 | 0.15 | 0.5 |

*3) Protocol:* In each session, subjects were given as much time as desired to familiarise themselves with the 3D environment and task, in a 'training mode' in 'Free Reaching' conditions. The Reaching Task was then completed under 'Free Reaching' and/or 'Robot Reaching' depending on the session as described above. Each target was presented for 10 successive attempts, in order (1-6), twice, for 120 total actions. Subjects were given as much time as desired to rest between actions, and an enforced longer break between each set of 10 actions, to minimise the effects of fatigue.

## B. Performance Metrics

To assess the subjects' movements, five commonly used kinematic metrics were applied on the wrist trajectories. These metrics were chosen for their respective complementarity and independence, and for their coverage of the different important aspects considered during a rehabilitation treatment: movement control, movement efficiency, movement quality and ease of movement [3].

The time period for each trial was considered to be the one second interval after the end of the countdown. Only the wrist position (the wrist sensor for the magnetic sensor and the wrist position for the exoskeleton) were considered.

*1) Peak Speed:* The speed was calculated in real-world coordinates, using a first-order Euler approximation on the position data. The peak speed was then determined as the largest value in this speed trajectory.

*2) Time of Peak Speed:* On identification of Peak Speed, the corresponding time stamp relative to the start of the movement was calculated.

*3) Smoothness:* The smoothness metric used was the Spectral Arc Length (SAL) Smoothness as defined in [6]. It was calculated using the wrist speed, after a re-sampling at 60 Hz (using a cubic spline interpolation), as:

$$\eta_{sal} = -\int_0^{\omega_c} \sqrt{\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega}\right)^2}\, d\omega, \qquad \hat{V}(\omega) \triangleq \frac{V(\omega)}{V(0)} \tag{1}$$

where $V(\omega)$ is the Fourier magnitude spectrum of the speed profile, $V(0)$ is the DC magnitude, and $[0, \omega_c], \omega_c > 0$ is the frequency band considered. In this study, $\omega_c = 20$Hz.

*4) Curvature:* Curvature was measured as the integral of the distance of the reaching trajectory from a straight line connecting the home position and the final position (at $t = 1$s). The distance of the trajectory from the straight line connecting the two points is calculated as $d_{str}(t)$. The measure of curvature is then given as:

$$C = \int_0^1 d_{str}(t)dt \tag{2}$$

*5) Accuracy:* Accuracy was defined as the shortest distance of the cursor to the target in virtual coordinates at $t = 1$s. A zero value indicated that the cursor was in the target. As the accuracy metric is dependant on the virtual space coordinates, it was only computed using magnetic sensor data, thus no comparison to the robotic data is given.

### C. Analysis

Two independent comparisons were made for this study. The first relates to the effect of the robotic exoskeleton on the movement of the subject – that is, the change in the kinematic reaching movement. For this comparison, the data captured by the magnetic sensors from the 'Free Reaching' trials is compared with that from the 'Robot Reaching' trials. The second comparison relates to the validity of the data captured by the robotic device, compared with that captured by the magnetic sensors. For this, the data captured by the magnetic sensors during the 'Robot Reaching' trials is compared with data captured by the robotic device during the same trials. For each metric, the comparison between the two data sets was tested using a Wilcoxon Signed-Rank Test [7].

## III. RESULTS

### A. Effect of the robotic exoskeleton on the movement of the subject

The values of each metric, calculated from the measurements of the magnetic sensor, computed for each block in the first and last sessions, and grouped for the 10 subjects and 120 trials, are presented in Fig. 4. The differences in the peak speed, time to peak speed, smoothness and accuracy were found significant ($p < 10^{-3}$).

Table II presents the average difference between the 'Free Reaching' and 'Robot Reaching' for each metric, as measured by the magnetic sensor, in the first and last sessions.

TABLE II
AVERAGE EFFECT OF ROBOT FOR EACH METRIC

| **Metric** ($unit$) | **First** | **Last** |
|---|---|---|
| Peak speed ($m.s^{-1}$) | -0.25 | -0.11 |
| Time to peak speed ($s$) | 0.10 | 0.09 |
| Smoothness (-) | -0.04 | -0.03 |
| Curvature ($m.s$) | -0.22 | 1.27 |
| Accuracy ($m$) | 0.025 | 0.007 |

### B. Validity of the data captured by the robotic device

The average difference between the metrics computed based on the magnetic sensor data and the robotic exoskeleton's data during the 'Robot Reaching' blocks of the first and last sessions are reported in Table III. None of these differences have been found significant.

TABLE III
DIFFERENCE BETWEEN DATA CAPTURED BY THE ROBOTIC DEVICE AND THE MAGNETIC SENSOR (MEAN $\pm$ S.D.)

| **Metric** ($unit$) | **First** | **Last** |
|---|---|---|
| Peak speed ($m.s^{-1}$) | $0.05 \pm 0.07$ | $0.05 \pm 0.10$ |
| Time to peak speed ($s$) | $-0.02 \pm 0.08$ | $-0.01 \pm 0.08$ |
| Smoothness (-) | $0.016 \pm 0.022$ | $0.018 \pm 0.028$ |
| Curvature ($m.s$) | $-0.30 \pm 1.3$ | $-0.17 \pm 1.3$ |

* Calculated as Robotic Data Metrics minus Magnetic Data Metrics

## IV. DISCUSSION

The results of this experiment suggest four distinct observations. Firstly, the data captured by the robotic exoskeleton is comparable to that of an external sensor. Secondly, the robotic exoskeleton has a significant effect on the movements of the subjects. Thirdly, the subjects are able to adapt to the environment presented by the exoskeleton in order to complete the task. Finally, evolution of non-task related metrics during the 'Robot Reaching' translates to similar changes in these metrics in 'Free Reaching'.

On this first observation, we note that Table III indicates that the metrics calculated on this robotic exoskeleton data and magnetic sensor data are equivalent. Furthermore, the Wilcoxon Test did not indicate a significant difference between these data sets. Thus, it is concluded that metrics calculated using the data of the robotic exoskeleton are accurate. As such, the remainder of the analysis is completed using the magnetic sensor data only, and it can be assumed that the robotic exoskeleton will produce similar results.

Secondly, the robotic exoskeleton can affect the 'natural' movements of the subjects. In both sessions, the Peak Speed and Time to Peak Speed are significantly reduced and increased respectively, when movements are performed within the exoskeleton. This indicates that the subjects found it more difficult to complete the movement within the exoskeleton. This was also confirmed by the majority of the subjects, who noted that the exoskeleton felt 'heavy'. With respect to movement quality, smoothness was also affected by the exoskeleton, suggesting that subjects performed more movement corrections or adjustments to successfully complete the task. However, the lack of difference in curvature suggests that the shape of the wrist trajectories is not changed in a global manner. These results align with those reported in [4] suggesting that exoskeletons can still apply undesired and uncontrolled forces on the subject's limb, even when designed to not affect movement. This imperfection of the robot's mechanical transparency suggests care should be taken when attempting to directly use the data for clinical assessment, as it may not truly reflect the capabilities of

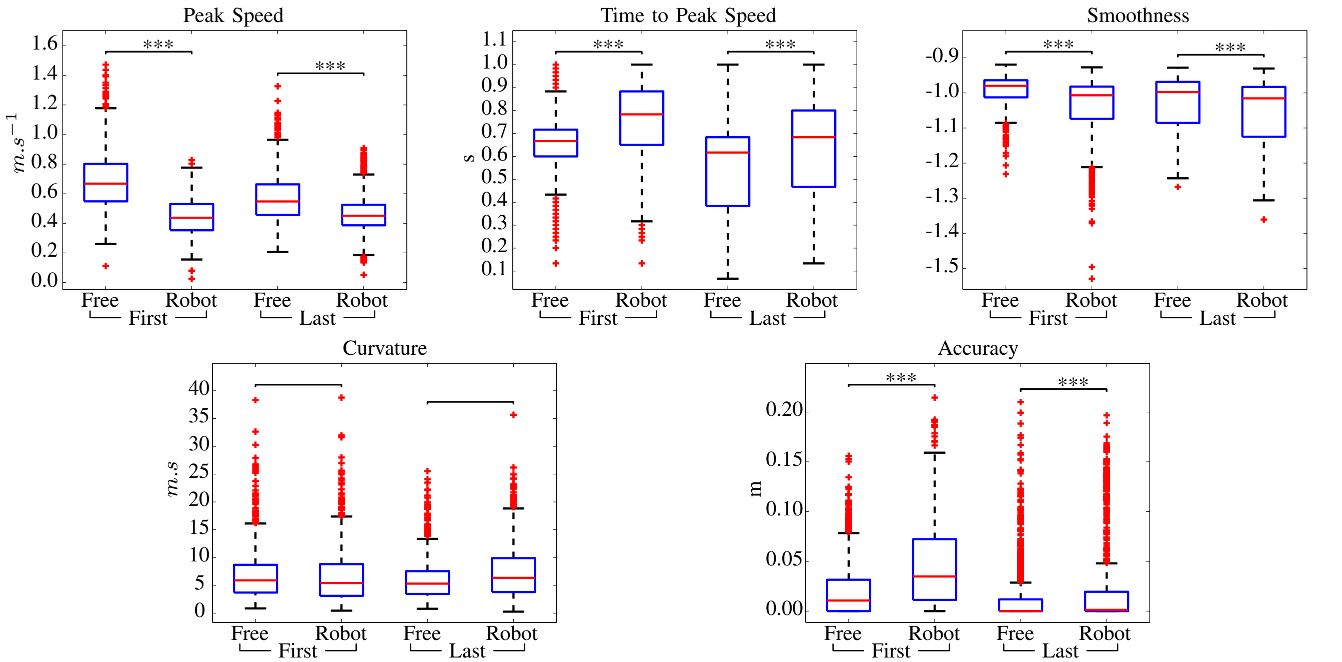


Fig. 4: Each metric as calculated on the magnetic sensor data for each block. *** indicates a significant difference between this pair of values ( $p < 10^{-3}$).

the patient when not in the robot, particularly for faster movements as in this experiment.

Thirdly, the differences reported on the accuracy metric suggest that subjects have more difficulty in completing a task within the exoskeleton compared to outside. However, this difference is reduced after several sessions within the robot. This result suggests that the subjects can learn to overcome the robotic perturbations to perform the task.

Finally, a global evolution of the other – non-task-related – metrics is observable after several sessions of ‘Robot Reaching’. This can be seen through the differences in the ‘Robot Reaching’ metrics in the first and last sessions. However, similar differences remain between ‘Robot Reaching’ and ‘Free Reaching’ within each session. This therefore suggests that the robotic data can capture the evolution of these metrics, despite the absolute values of these metrics not corresponding to the ‘Free Reaching’ performance. Further analysis may be performed on these differences to determine the differences due to the (1) learning of the task, and (2) adaptation to the robot perturbation.

## V. Conclusion

In this experiment, the uncontrolled mechanical effects of the ArmeoPower affected the reaching trajectories of the subjects, suggesting that assessments of patients’ movement capabilities using data captured by this robotic exoskeleton should be approached with caution. Such uncontrolled effects should also be considered when basing assessments on movements in other exoskeleton devices. Nevertheless, the robotic data did reflect an evolution of classical movement metrics and may thus be used for inter-robot comparisons. This may be incorporated into a clinical evaluation if the bias induced by the exoskeleton is accounted for. Furthermore, the data captured by the robotic device accurately represented the movements themselves, thus this data can be used calculate accurate metrics. Further investigations are required to determine the relative role of learning of the robotic perturbation against changes in movement strategies for the same task while in a robotic exoskeleton.

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