Evaluation of a gamified upper-arm bimanual trainer for stroke patients - A healthy cohort study

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Abstract— The current study aims to evaluate the bimanual trainer, ArmAble, using electrophysiology and kinematic data from a healthy cohort, that can help in creating a reliable rehabilitation schema.

We use muscle activation patterns recorded through electromyography in healthy subjects, in order to understand the effect on synergies and activation patterns while using a bimanual trainer. We recorded electromyography from six muscles on either side (including four anti-gravity muscles) and kinematic data, while the subject uses the bimanual trainer to understand the muscular activation in the upper limbs. Experimental conditions included different complexity of reaching tasks and different inclinations. We computed the muscle output as quantified by RMS values and inter-muscular coherence, which denotes common cortical drive and coordination between muscles. While inclination did not have a significant effect on RMS, there was a marginal yet non-significant effect on IMC. Whereas the complexity of the reaching task did affect the RMS, while it did not affect IMC. We discuss these results in the context of game design principles for neuro-rehabilitation.

Keywords- Electromyography, bimanual training, intermuscular coherence, RMS-EMG.

I. INTRODUCTION

Stroke is a neurological disorder that causes functional deficits in the motor system, among others, limiting the ability to perform volitional motor action [1]. Patients undergo stroke rehabilitation, a motor recovery process to restore lost functions [2], [3]. Over the years, multiple interventions have been developed for stroke rehabilitation, which are broadly generalized or target-specific. In this work, we study the bimanual rehabilitation strategy for the upper extremities, which involves task-based repetitive activity to regain motion function. Various studies show that task-oriented training is successful if started at the acute stage for acute and sub-acute stroke patients [4]–[6], while few studies have also reported limited success with task-based, especially when rehabilitation is not initiated at an early stage [7]. Although task-based training is effective, there exists the issue of lack of motivation in patients to perform repetitive exercises [8]–[10].

In this regard, the gamification of the paradigm has shown to improve engagement and motivate patients to perform repetitive exercise paradigms.

In this study, we aimed to understand bimanual training in a functional manner in a healthy cohort. We used ArmAble, a bimanual neuro-rehabilitation device that allows the subjects to move their arms in the X-Y plane while playing interactive games. We recorded electromyography (EMG) and kinematic data from the upper arm while subjects engaged with the device.

Typically, stroke recovery is assessed using Fugl-Meyer scoring, where patients are asked to perform various forms of limb movements and measure captures the extent, synergy and speed of movement of limbs. In an objective sense, these are captured in the gross muscular output, co-ordination between muscle groups and limb kinematics. The gross muscular output can be measured by the root mean square (RMS) of the EMG data, while the muscle co-ordination and the cortical drive for synergistic movements is known to be signified by the beta-band (12-30 Hz) inter-muscular coherence (IMC) [11]–[13]. Thus, RMS and IMC were chosen apriori, as they appropriately and objectively explain the clinically relevant scoring schema for assessing the recovery of a stroke patient.

II. MATERIALS AND METHODS

A. Cohort

The study was approved by the Institutional Ethics Committee (IEC) of the Indian Institute of Technology Hyderabad. The cohort consisted of twelve healthy subjects (two females; age: 25.29 ± 0.89 (Mean ± Standard Error of the Mean (SEM)). Subjects were comfortably seated in a chair. Informed consent was taken from the subjects prior to the experiment and were allowed to withdraw from the experiment at any point in time. Demographic and other data such as height and upper limb segment lengths of the subjects were also collected.

B. Bimanual Trainer

ArmAble is a game based bimanual neuro-rehabilitation training device for the upper extremities and was developed by *BeAble Health*, Hyderabad. The device consists of a handle over a platform allowing motion of the handle across XY-plane bi-manually. The platform of the device can also be inclined at different angles to increase the load on the upper extremity and placed at various heights to suit the height of the subject. Games designed are culturally appropriate, innocuous, and have three difficulty levels.

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C. *Experimental Paradigm*

The three different patterns are as follows (refer Fig. 1):

- Point to point circle: A simple reaching pattern game where the objects on the screen are displayed one after the other in a circular pattern either in clockwise or anti-clockwise, in a randomized manner. Data was recorded at two inclinations (0 °, 30°).
- Point to point octants: A simple reaching pattern game where the objects are displayed from the center to a random point covering all the eight octants of the planes per cycle. Data was recorded at two inclinations (0 °, 30°).
- Point to point Random: Unlike the above two known patterns, the reaching objects in this game are utterly randomized in the plane, making it a complex pattern. The subject has to reach from one point to another based on the objects. Data was recorded at three inclinations (0 °, 15°, 30°).

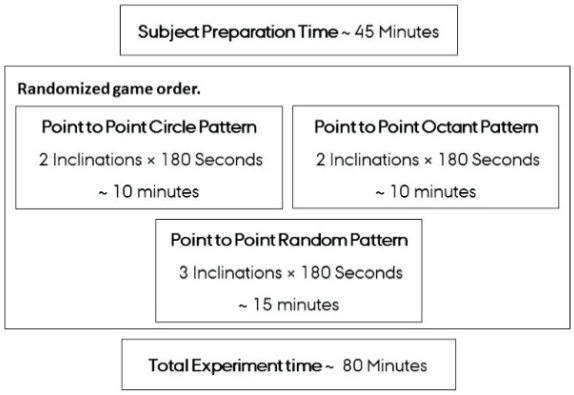

Fig. 1: Experimental Paradigm followed for data acquisition. Each block was randomized. Subjects performed three tasks – Point to point circle (two inclinations 0 °, 30°), point to point octant (two inclinations 0 °, 30°), point to point random (three inclinations 0 °, 15 °, 30°)

As the pattern of the objects for reaching in the first two games is linear and shape-based, namely octant and circular reach, we classified them as a simple reaching task. The third entails reaching to random points on the board, hence classified as a complex reaching task. All subjects played the same games but in a randomized order.

In the first two sets of simple reaching tasks, the subject was asked to perform ten iterations of the specified pattern and took 150 s (±30). In the third task of complex reaching, the objects were displayed for a fixed time of 180 s.

D. *Data Acquisition*

1) Electromyography

We recorded EMG of muscles of the upper limb and shoulder using active g.Scrabeo electrodes (unipolar, gel-based; refer Fig 2 (b)) coupled to a g.HiAmp amplifier (g.tec GmBH, Austria), while the subject used the rehabilitation device. The selection of muscles to record EMG was based on the Fugal-Mayer assessment scale. EMG was recorded from 6 sets of muscles from both the upper limbs after appropriate palpation, namely, Trapezius, Deltoid, Triceps Brachii, Biceps Brachii, Flexor Digitorum Superficialis, and Extensor Digitorum. Electrocardiographic (ECG) data was also acquired using the lead II configuration. ECG data was recorded for artifact rejection purposes. Common reference was placed in the earlobe and the ground electrode at ulnar styloid. The impedance of the electrodes was found varying between 30 kΩ to 120 kΩ.

Raw data from the g.tec HiAmp Research system was acquired and saved using an acquisition model build in Simulink (MATLAB R2017b, Mathworks Inc., USA). The EMG data was acquired at a sampling frequency of 1200 Hz, filtered using a Butterworth 8th-order Band-pass filter (>5 Hz) and a Butterworth 4th-order notch filter (48 Hz-52 Hz).

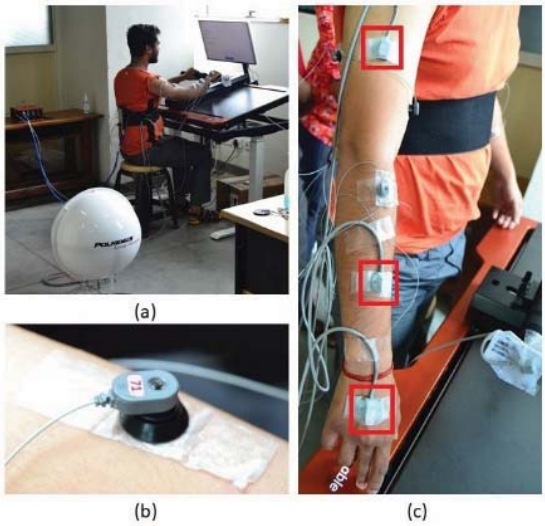

Fig. 2: (a) Experimental setup of the subject playing a game on the bimanual trainer. (b) g.tec Scrabeo active wet-type electrode used for the recording of the EMG data (c) Polhemus electromagnetic sensors and corresponding placement over the upper limb.

2) Biomechanical Data

The Polhemus Liberty electromagnetic tracking system was used to record continuous position data from the right upper limb (refer Fig 2 (c)). Three sensor channels were placed on the right upper limb approximately between the third distal phalanx tip and styloid; styloid and epicondyle; epicondyle and acromion, respectively. The fourth sensor was initially used as a stylus for setting up the origin axes, and digitization of the upper limb sensors and then placed at the handle of the ArmAble device so as to record the handle position alongside arm movements [14]. Real-time biomechanical data acquisition was performed at 240 Hz and was later up-sampled and rendered at 1200 Hz [15]. Trigger data from the ArmAble device was recorded by the Polhemus tracker to extract the position data during the tasks.

E. *Data Processing*

1) Processing of Biomechanical Data

The biomechanical data was smoothened by moving average technique (span of 5 points) to suppress jumps in the recorded data and plotted. Position co-ordinates data from sensor 1 (placed between the distal phalanx tip and

styloid) were used to plot the arm movement trajectories from the biomechanical data. Principal component analysis (PCA) was performed, and data was projected onto the first two principal components to reduce the pitch axis and render the trajectory on a 2D plane (Fig. 3).

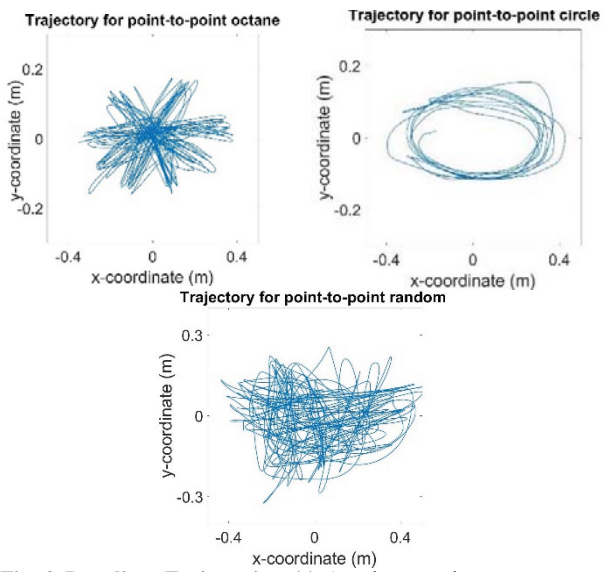

Fig. 3 Paradigm Trajectories: (a) A point to point octant pattern reaching eight octants of a plane (b) Point to point circle pattern moved clockwise or anti-clockwise randomly (c) Point to point random movement covering the entire plane. A PCA was performed and trajectories projected onto the first two principal components to render a 2D trajectory.

2) Pre-processing of EMG data

The artefact rejection, processing, and analysis of the data were performed using the Fieldtrip toolbox [16]. Data segments corresponding to the data acquired before and after the start and stop of the game were removed based on triggers set by the ArmAble.

The data was initially filtered using a Butterworth 6th order low pass filter at 150 Hz, and a DFT filter at 50 Hz, 100 Hz & 150 Hz was deployed.

Independent Component Analysis (ICA) algorithm was used to suppress the ECG artifacts recorded in the EMG channels, where components with maximal ECG artifact were rejected based on visual inspection [17], [18]. The processed EMG data was epoched into arbitrary segments of 1 s each, which was then passed onto data analysis.

3) Analysis of EMG data

a) Inter-Muscular Coherence (IMC)

The frequency spectrum of the time series trial data was computed (Eqn. 1) by the multitaper frequency transformation (*ft_freqanalysis*, '*mtmfft*', smoothing bandwidth = 1 Hz) using the conventional hanning taper for a frequency range of 1 Hz to 150 Hz.

Inter-muscular coherence (IMC) at a beta frequency range (12-30 Hz) between the various muscle combinations were computed to analyse the connectivity between two muscles. IMC determines the degree of coupling between two EMG signals *x(n)* and *y(n)*, providing an output between 0 (no linear dependency) and 1 (perfect linear dependency) for each frequency. Let $X_n(f)$ and $Y_n(f)$ be the Fourier transform of the nth segment of *x(n)* and *y(n)*, by defining.

$$P_{xy}(f) = \frac{1}{N}\sum_n X_n(f)Y_n^*(f) \qquad \text{(Eq. 1)}$$

$$Coh_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \qquad \text{(Eq. 2)}$$

b) Root Mean Square (RMS)

The RMS values for each muscle, reflecting the muscle output, were calculated as shown in Eqn. 3.

$$RMS = \sqrt{\frac{1}{n_2 - n_1}\sum_{N=n_1}^{n_2}[F(N)]^2} \qquad \text{(Eq. 3)}$$

F. Effect of complexity and inclination

To quantify the effect of complexity alone, metrics were averaged in simple (point to point octant, circle) and complex (random reach) tasks and across all other conditions (inclinations). Whereas, to quantify the effect of inclination alone, metrics were averaged in different inclinations across all other conditions (task complexity). We repeated this analysis with a subset of the data with anti-gravity muscles (Trapezius, Deltoid, Triceps, and Biceps).

G. Statistical analysis

We performed log transformation on the IMC, RMS values and used paired t-test to analyze the statistical significance of an effect of complexity and inclinations across all muscles and anti-gravity muscles alone. Significance criterion was set at 95%.

III. RESULTS

A. Effect of complexity overall muscles

The inter-muscular coherence and RMS was calculated to understand the effect of complexity across all the muscles. There was a significant effect of complexity on the RMS ($t = -2.384$; $p = 0.036$) while no significant effect was noted on the inter-muscular coherence ($t = 0.478$; $p = 0.642$; See Fig.4 (a) and Table. 1).

B. Effect of Inclination across all muscles

The IMC and RMS was calculated to understand the effect of inclining the plane of the movement across all muscles. There was neither a significant effect of inclination on the IMC ($t = 1.826$; $p = 0.095$) nor on the RMS ($t = 0.019$; $p = 0.9851$; See Fig.4 (b) and Table. 1).

C. Effect of Inclination across anti-gravity muscles

We found no significant effect of inclination in the complex task on the IMC between anti-gravity muscles ($t = 1.378$; $p= 0.195$), and there was no significant effect of inclination on the simple task ($t = 1.620$; $p = 0.1335$). Similarly, we found no significant effect of inclination on the RMS on either the simple ($t = -0.751$; $p = 0.468$) or the complex task ($t = 1.378$; $p= 0.195$; See Fig.4 (c) , (d)).

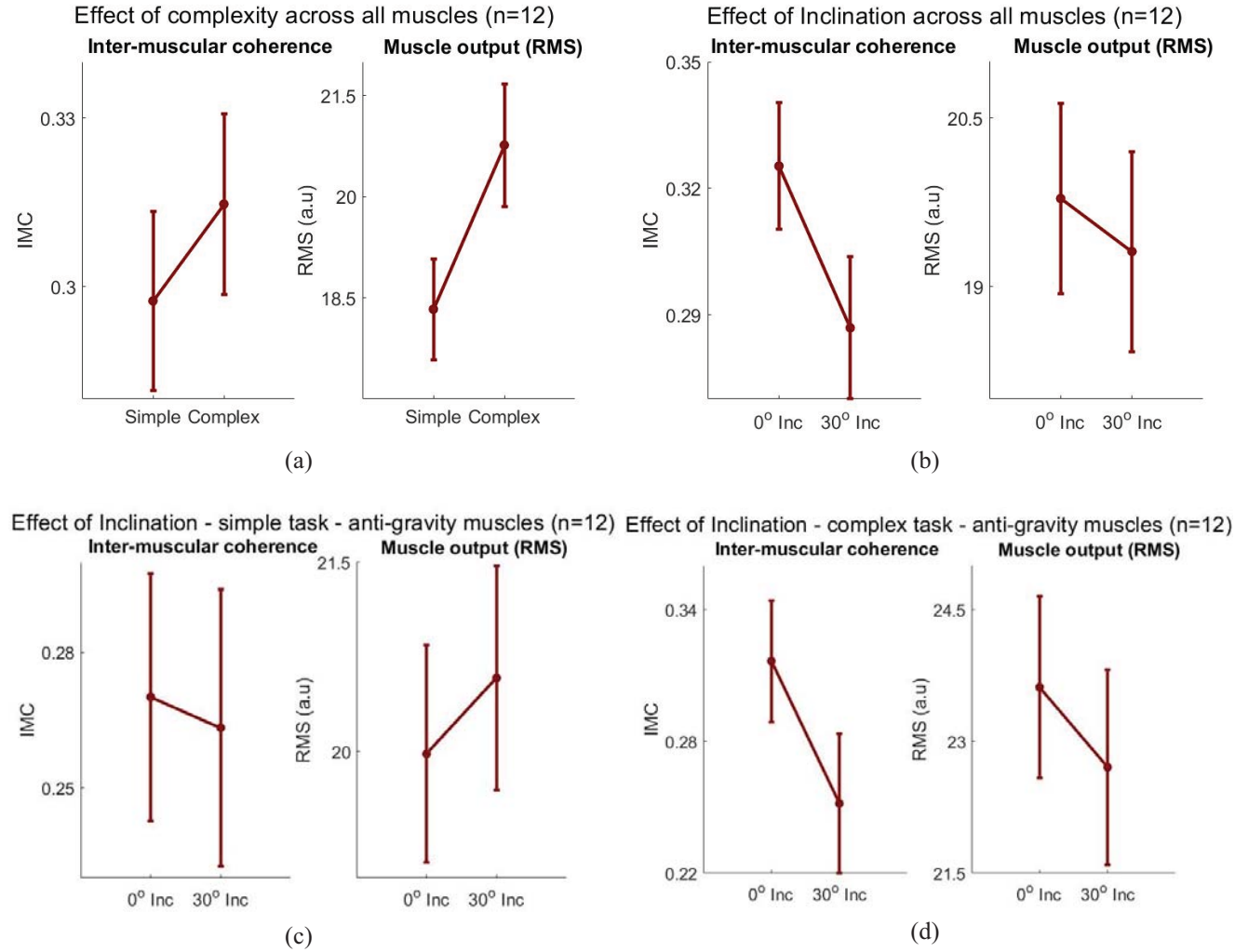

Fig. 4: The plots show the grand average of IMC and RMS for different conditions. **(a) Effect of complexity across all the muscles:** Statistical testing showed that while there was an effect of reach complexity on the RMS (t = -2.384; p = 0.036), it was not significant on the IMC (t = 0.478; p = 0.642). **(b) Effect of Inclination across all the muscles:** Statistical testing showed that there was no effect of inclination on the IMC (t = 1.826 ; p = 0.095) nor on the RMS (t = 0.019 ; p = 0.9851) **(c) Effect of Inclination across the anti-gravity muscles during simple reach task:** Statistical testing showed that there was neither an effect of inclination on the IMC during the simple task (t = 1.620; p = 0.1335), nor on the RMS (t = -0.751; p = 0.468). **(d) Effect of Inclination across the anti-gravity muscles during complex reach task:** Statistical testing showed that there was neither an effect of inclination on the IMC during the complex task (t = 1.378; p= 0.195) nor on the RMS (t = 0.623; p = 0.546).

TABLE I. Summary values: Means and SEMs of metrics are shown condition-wise.

Muscle	Tasks		IMC	RMS (a.u)
All muscle	Simple		0.2975 ± 0.0160	18.3316 ± 0.7476
	Complex		0.3147 ± 0.0160	20.7653 ± 0.9106
	0° Inc		0.3253 ± 0.0150	19.7842 ± 0.8486
	30^0 Inc		0.2869 ± 0.0168	19.3126 ± 0.8899
Anti-gravity muscles	Simple	0° Inc	0.2701 ± 0.0275	19.9827 ± 0.8603
		30^0 Inc	0.2633 ± 0.0307	20.5853 ± 0.8864
	Complex	0° Inc	0.3166 ± 0.0276	23.6176 ± 1.0343
		30^0 Inc	0.2519 ± 0.0317	22.7078 ± 1.1092

IV. DISCUSSION

The main aim of the study was to functionally assess the bimanual trainer ArmAble, using electrophysiology and kinematic data in a healthy cohort. We intended to understand the intermuscular coherence and gross muscular output it entrains in healthy individuals in order to potentially improve the game design.

RMS, a correlate of gross muscular activity, was not affected by an increase in inclination either across all muscles nor a subset of anti-gravity muscles. It would be expected that increased loading due to increased inclination would lead to an increased RMS [19], [20]. Instead, the complexity of the task had a significant effect on RMS. Visual inspection of the kinematic data revealed that the subject had to displace their upper limb to a lesser extent when inclined compared to the 0^0 inclination. Whereas, during the complex task, the subjects displaced their upper limb to a larger extent compared to a simple reach. Hence,

we infer that greater displacement might play a key factor in increasing the motor output.

While inclination did not affect the RMS, it did have a non-significant yet moderate effect on IMC (p=0.09. t=1.7). IMC in the beta-band is known to signify a common cortical drive from the cortical areas to synergize and coordinate movements in the periphery. Various studies have shown that they could point to an aspect of sensorimotor processing and might be a channel to maintain stable motor output [13], [21], [22]. Hence, though non-significant, we suspect in healthy individuals, increased co-ordination between muscles might be the mechanism to handle larger loads [23].

A more fine-grained analysis, using kinematic information, will help us to understand better the effect of the bimanual trainer on muscle output, coordination and synergy between muscles in various conditions. Results from this study can be used as a benchmark for better game design deriving from the activation patterns and synergies entrained. These results can also be used within a machine learning framework to provide personalized prescriptions on exercise regimes and also for prognostic purposes wherein clinical assessments can be derived from the volitional movements performed, together contributing to improved rehabilitation outcomes.

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