An sEMG-Driven Multiple DOFs Interactive Games Based Rehabilitation Protocol for Stroke Patients: Assessing Real-Time User Performance Feedback

Ammar Shahzad, Muhammad Mustafa Khan, Muhammad Farhan, Hamza Suhaib Qarni,Javaid Iqbal, Imran Khan Niazi, Asim Waris and O. Gilani

***Abstract*—Interactive home-based rehabilitation (HBR) techniques have been in growing demand due to the prevalence of chronic diseases and the need for more accessible and flexible rehabilitation options. Video Game based therapy (VGT) is a commonly employed interactive HBR technique for upper limb poststroke patients. However, most of the studies done on VGT lack clinical usability and real-time user performance feedback. This study aims to probe the effectiveness of interactive 2D game training of the hemiparetic hand of stroke patients through the proposed rehabilitation protocol. Real-time performance is measured using Fitt's law to quantify the proposed model's effectiveness. Seven performance parameters: score, throughput, completion rate, path efficiency, overshoot, completion time and joint angles measured via goniometer, were used to assess the useability of the proposed 2D game-based rehabilitation protocol. Ten healthy subjects and two chronic phase stroke patients participated in a three-week study. For the stroke patient in the 1 DOF game, it was found that, on average, the completion rate (73.33 ± 11.55) and score (76.67 ± 15.28) on the last day of the protocol was significantly better $(P < 0.05)$ than the completion rate (33.33 ± 5.77) and score (43.33 ± 5.77) of first day. In 2 DOF game, on average, the completion rate (73.33 ± 5.77), overshoot (26.67 ± 5.77) and throughput (0.267 ± 0.057) on last day of the protocol was significantly higher $(P < 0.05)$ than the completion rate (16.67 ± 15.28), overshoot (83.33 ± 15.28), throughput (0.069 ± 0.009) of first day. The results suggest that the proposed protocol has great potential for providing interactive HBR for stroke patients.**

***Index Terms*—Electromyography, Fitts' Law, Game Control Interfaces, Hand gesture recognition, Home-based rehabilitation, Machine learning, Pattern recognition, Real-time classification**

I. Introduction

According to the Centers for Disease Control and Prevention (CDC), stroke is a primary cause of death, and severe long-term disability for Americans, with annual stroke-related costs in the United States being approximately $53 billion [1]. In the United States alone, over 795,000 individuals experience a stroke annually, almost two-thirds requiring rehabilitation [1]. Similar figures are reported from other countries according to which more than 75% of acute stroke survivors loses skills related to arm and hand movement [2]. Furthermore, according to the World Health Organization's World Report on Disability, the global estimate for disability is increasing due to population ageing and the fast spread of cardiovascular diseases, with stroke as the primary cause. In lower and middle-income countries, non-communicable chronic diseases (mainly stroke) are estimated to account for 66.5% of all years lived with disability. These disabilities usually correlate with social and economic disadvantages. Accessible rehabilitation techniques can effectively alleviate these socioeconomic disadvantages by enabling stroke patients to reinstate their functional health.

Rehabilitation refers to a set of measures that assists people with disability to regain, improve and maintain individual functioning to acquire maximum self-sufficiency [3], [4] In the recent couple of decades, due to the advent of machine learning (ML) and improved assistive technologies, there has been a continuous uptick in the usage of Electromyography (EMG) signals for human-computer interaction (HCI), prosthetics, virtual reality, and many other fields to ameliorate the users' quality of life. Moreover, there has been a growing trend towards incorporating technology in rehabilitation-based therapy to alleviate patient comfort. The exercises in these rehabilitation therapies should be user-friendly and engaging to enhance their effectiveness [5], [6]. Adding competitive elements and scoring mechanisms can help achieve specific rehabilitation goals [7], [8]. Additionally, the exercises must be flexible and allow for adjustments based on the patient's condition.

Post-stroke rehabilitation is a lengthy process that typically requires intensive care and hands-on physical therapy for a longer duration after the initial concussion. Furthermore, due to the inadequate global healthcare sector, stroke patients receive limited therapy and are discharged sooner [2]. Therefore, much effort has been focused on developing rehabilitation techniques that allow stroke patients to practice physical exercises in a home-based environment with the minimal involvement of a therapist [7]–[9]. HCI-based rehabilitation therapies, such as Game Therapy, Virtual Reality (VR), Mixed Reality (MR) and Augmented Reality (AR) therapy, allow the stroke patient to practice rehabilitation exercises in a home-based environment and have proved superior to the conventional treatment techniques [10]–[14].

AR and VR commonly use input sensors allowing users to navigate and interact with the virtual environment (e.g., joystick, glove for capturing finger or hand movements) and output devices that send the sensory information to give the user an immersive experience (e.g., VR glasses, VR helmet, and Head-mounted displays) [15]. Immersive VR technology aims to produce computer-generated environments that replace real-world sensory experiences with digital ones, providing users with the feeling of "presence" – that refers to an

This research has been supported in part by National University of Sciences and Technology (NUST), sector H-12, Islamabad under Research Grant (Project # NUST-22-41-48).

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illusion of being physically present in the environments rendered by VR while adhering to the physical laws and psychosocial expectations [16]. AR aims to overlay the virtual objects with the physical world providing users with a sense of presence — in AR, it can be defined as "informed continuity" [14], [15].

The ultimate goal of both VR and AR is to create an accurate and reliable simulation of the real world that coherently generates a sense of presence in the users [17]. If the virtual environment fails to appear coherent, it will be perceived as unrealistic, resulting in a poor user experience. This can lead to the failure of the simulation to have positive effects and instead can cause negative effects such as cybersickness (i.e., a feeling of bodily discomfort and malaise caused by the discrepancy between perceived and expected sensory signals) [14], [15], [17]. Furthermore, the high cost associated with head-mounted displays (HMDs), cellphones, workstations, and gaming platforms make VR and AR-based rehabilitation therapies unfordable for a vast majority of stroke patients, specifically in developing and third-world countries.

Video Game-based therapy (VGT) is another interactive rehabilitation technique that allows stroke patients to practice rehabilitation exercises in a home-based environment with the least therapist intervention. Plenty of research has been done on building video games-based rehabilitation protocols [7], [11], [18], [19]. However, more studies have yet to be devoted to assessing the useability of sEMG-driven VGT protocols for improving stroke patients' hand mobility with real-time user performance feedback. An effective means for quantifying the usability of a control system is via Fitts' Law. Fitts tells us that any human motor task conveys a finite amount of information limited only by the control system's capabilities and exhibits a tradeoff between speed and accuracy [20]. Fitts' Law approach has been validated for both sEMG and intramuscular EMG control [21], [22], and it is also used in many applications, such as robot-assisted post-stroke rehabilitation [23].

In this study, we developed an interactive experimental rehabilitation protocol that can be used for rehabilitation of poststroke patients with upper limb extremities in a home-based environment. Most studies performed on VGT do not include mechanisms for assessing real-time user performance feedback. This makes them less suitable for clinical usability, which requires real-time user's performance feedback to assess patients' conditions over time. In the given study, the useability of the proposed rehabilitation protocol is determined using both the real-time performance parameters based on Fitts' Law approach and offline parameters (i.e., the joint angle measured via goniometer). For better quantification of the proposed technique, a three-weeklong protocol was followed, one week for ten healthy subjects and two weeks for stroke patients.

II. Materail and Methods

The implementation of the proposed protocol comprises five stages:

1) Data acquisition from the Myo armband
2) Data preprocessing
3) Feature extraction
4) Gesture classification
5) Sending the classifier output to the game interface

as depicted in the Fig. 1. All the stages are elaborated on in the sections below.

A. Participants and apparatus

Two-stroke patients and ten healthy intact subjects (10 males; 2 left-handed, 8 right-handed; age 22 ± 3.4 years) voluntarily participated in the study. Details of the stroke participants are shown in Table I. The surface EMG data was recorded via Myo armband's

TABLE I
Demographic data of stroke patients

Demographic Data		
Characteristics	Patient (1)	Patient (2)
Age	57	43
Gender	Male	Male
Type of Stroke	Hemorrhagic stroke	Hemorrhagic stroke
Side Effected	Right hemiplegia	Right hemiplegia
Time since Stroke	2 Years	6 months
Undergoing Physiotherapy	No	Yes
Numbness in Hand	No	slight
Active Movemensts		
Wrist Flexion	Present	Present
Wrist Extension	Present	Limited
Hand Close	Present	Present
Wrist Radial Deviation	Present	Absent
Wrist Ulnar Deviation	Limited	Absent

(MYO) wireless surface electrodes. MYO is a battery-powered wearable device developed by Thalamic Labs Inc., which comprises eight circularly arranged sEMG electrodes. It has three modes of data acquisition, (i) 50 Hz filtered data (ii) 200 Hz rectified data (iii) 200 Hz raw data. It also has a built-in 9-degree of freedom Internal Measurement Unit (IMU) for detecting the forearm movements in the 3D space with a Bluetooth Low Energy (BLE) transmission module for data transferring [24]. In this study, only the raw sEMG data is acquired at a sampling frequency of 200 Hz. Due to MYO's robust features, it is extensively used in biomedical research and for biofeedback purposes [25]–[27].

B. Data acquisition protocol

A well-defined data acquisition protocol in-line with the World Medical Association's (WMA) Standard operating procedure and Declaration of Helsinki [28], approved by the Research Ethical Committee of the National University of Science and Technology (approval no: M-20221206), was established for data recording shown in Fig. 2. Prior to the data acquisition, each subject was given a thorough oral explanation of the experiment, safety precautions, and associated risks. Moreover, the stroke patients were also given their informed written consent form before the data recording. The patients were instructed to sit in a comfortable armchair while keeping their arms vertically relative to the floor. Myo armband was placed on the forearm with special care so that the electrodes always lie at 5 centimeters distance to the elbow. The subjects then performed the gestures according to the movements prompted on the screen.

C. Experimental procedure

A three week-long experimental protocol was designed for both stroke patients and healthy subjects, wherein data was recorded and tested against the performance parameters for five working days during each week. Healthy subjects were evaluated for the validation of Fitt's law test for the given study. Each day three sessions were performed with a 1-hour gap between each session. Every motion was tested five times in each session for 1 and 2 DOF games, so 10 targets were to be reached per session. Trial sessions wee carried out to accustom the subjects to the custom-made game user interface as shown in Fig. 3.

A single session consisted of 5 repetitions of 6 dissimilar hand gestures (wrist flexion, wrist extension, hand close, wrist radial deviation, wrist ulnar deviation and rest). Each single gesture data recording lasted for only 5 seconds. Furthermore, a total rest time of 10 seconds was also given after the completion of each session for

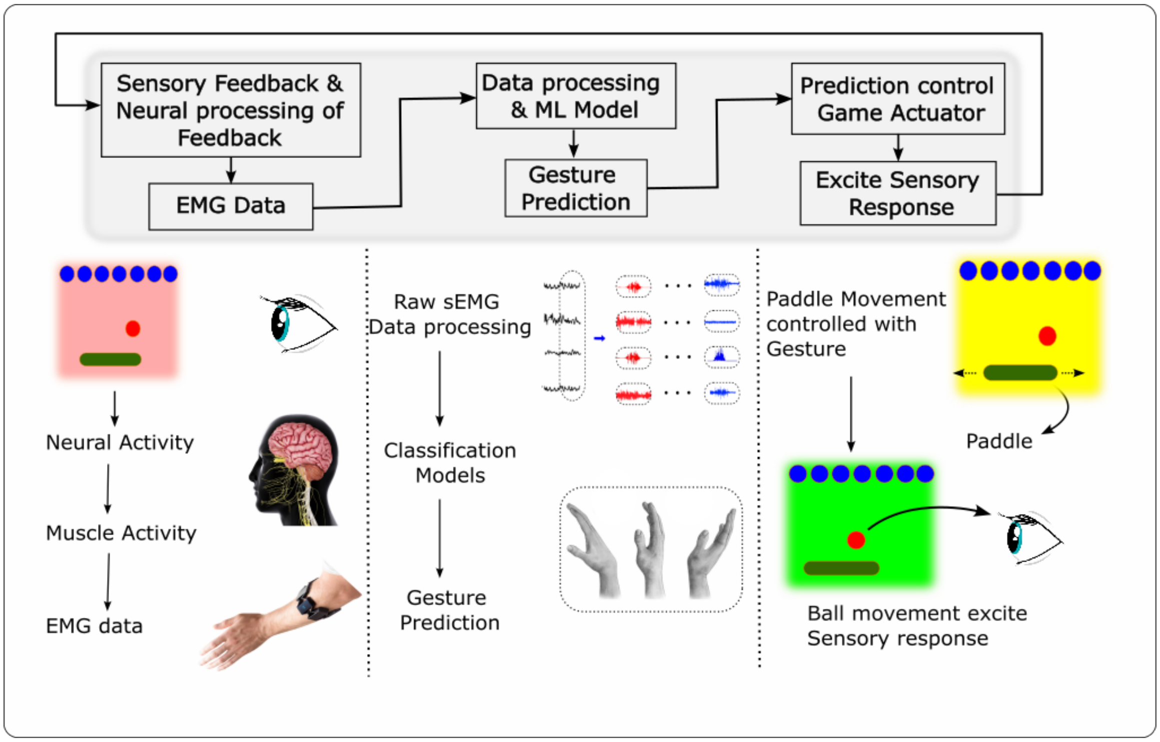

Fig. 1. Flowchart showing protocol setup (a) Visual pathway to muscle actuation (b) Summary of ML model training (c) Paddle movement according to the predicted gesture, feedback to visual pathway

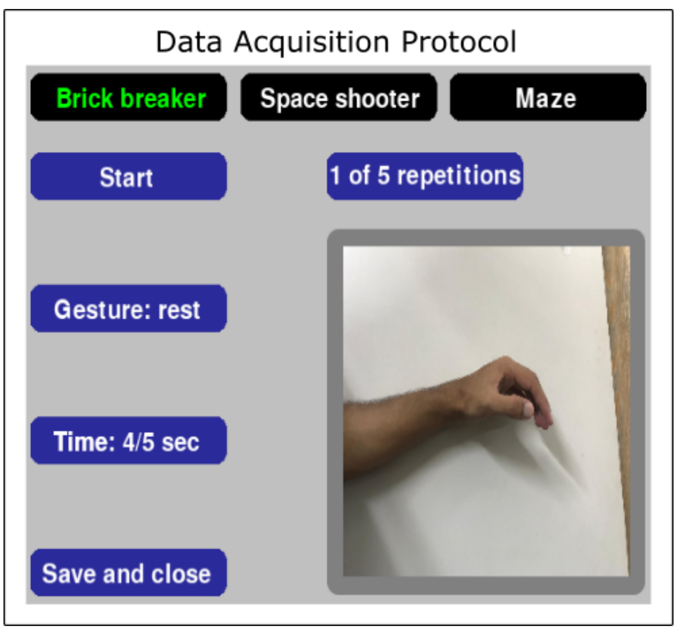

Fig. 2. GUI for data acquisition and offline training

avoiding muscular fatigue [29]. After data recording, the signals were processed, and the ML model was trained on that data followed by the real-time evaluation using video games. Given the distinct recovery phases of a stroke and the mobility constraints associated with each stage, multiple games were designed to make the proposed protocol more adaptable for patients in any phase. In the given study stroke patients were tested only against the games in accordance with their hand mobility.

In both 1 DOF and 2 DOF games, the participants were tasked to manoeuvre the avatar from its starting position to a target location, shown as a red box of width (W) located at a distance (D) from the pad. The target locations are predefined, and the same ten positions are used to keep index of difficulty (ID) the same throughout each session. In order to keep the starting distance, the same, the avatar is moved to the mean position after each trial. The Fits law was used for the ID calculation for each target location based on its distance D from its target and the width W of the target. Table II shows a different combination of target distances and widths. Equation (1) was used for ID calculation.

$$ID = log_2\left(\frac{D}{W} + 1\right) \tag{1}$$

During the real-time evaluation for stroke patients, three sessions were performed per day. To quantify the performance of the proposed system, seven performance parameters were used: score, throughput, completion rate, path efficiency, overshoot and joint angle measured via goniometer. For the trial to be considered successful the subjects were required to hold the pad within the target box till the completion of that trial (dwell time, hitting the ball) [22], [30].

D. Performance parameters

The real-time performance of the subject in a 1 DOF game is evaluated using overshoot, completion rate, score, and throughput, while in a 2 DOF game, it is evaluated using throughput, completion rate, completion time, and overshoot. The overshoot metric is defined as the ratio of the number of times the avatar enters the target location but fails to stay there to the total number of attempts made by the participant in one session. Completion rate signifies the overall success of the subjects and is expressed as the fraction of trials finished successfully within a single session [31]. Scores depict the numerical value of the subject successfully hitting the target (i.e., ball) in a single session. Throughput is the mathematical ratio between ID and the time taken to complete the trial. It is a means for determining

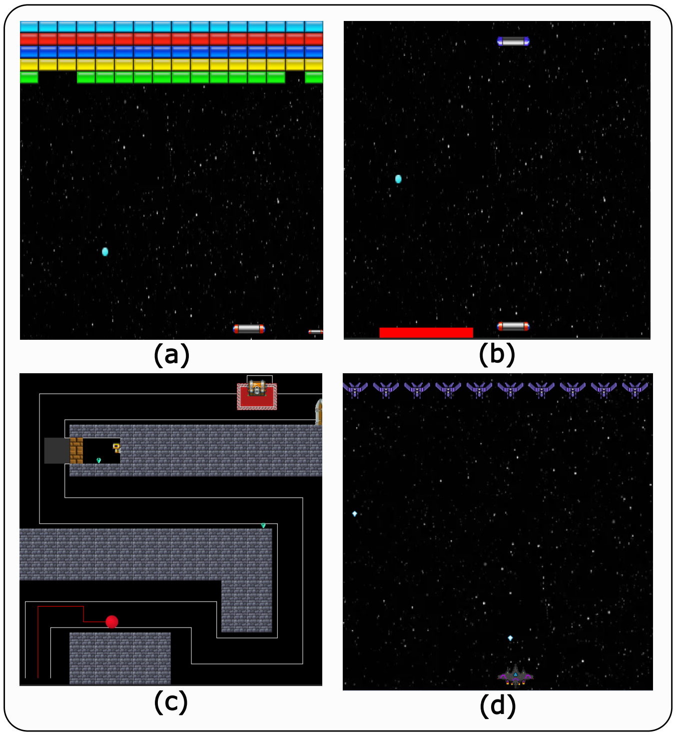

Fig. 3. Proposed framework for sEMG-based upper limb rehabilitation. (a-b) Brick Breaker, (c) Space Shooter, (d) Maze

a subject's capacity to transmit information via a command source in relation to a specific task [20], [21]. Higher throughput shows a fast response. Path efficiency is evaluated only in 3 DOF game and is computed by dividing the distance travelled inside the ideal path by the total distance travelled [32]. Joint angle measurement via goniometer is the only offline check on the validity of the proposed rehabilitation protocol [33].

III. Data Processing

The insight into the data processing carried out in this work is described below.

A. Data Segmentation

Both overlapping and disjoint sliding windows have been used in the studies for EMG data segmentation. However, it has been found that generally, an overlapping sliding window, with an overlap of 50%, gives the most accurate result [26]. The classification accuracy of the pattern recognition model generally increases with the size of the window lengths [34]; However, the greater the window size, the more time it takes in a real-time classification of a hand gesture. The total delay for the real-time classification should be less than 0.3s [35]. Hence the window length should be set to a smaller value. Nevertheless, a small window size can decrease the model performance by increasing feature variance [36]. The optimum sliding window length with 50% overlap is 150 to 200 ms [36], [37] which meets the standards for the time lag in traditional controllers for multiple-state amplitude control. In this study, a sliding window of length 150 ms with 73% overlap was run through the entire normalized raw data to get the best performance of the classifier.

B. Feature Extraction

The sEMG signals are categorized as time series structured data that generally have three nonparametric feature extraction approaches:

TABLE II
Combinations of widths (W) and distances (D) for Brick Break and Space Shooter with resulting index of difficulty (ID)

Space Shooter			Brick Breaker		
D	W	ID	D	W	ID
34	110	0.39	50	243	0.27
57	110	0.60	181	243	0.80
69	110	0.70	302	243	1.17
79	110	0.78	342	243	1.27
99	110	0.93	276	243	1.09
101	110	0.94	127	243	0.61
155	110	1.27	342	243	1.27
159	110	1.29	228	243	0.95
178	110	1.39	369	243	1.33
186	110	1.43	176	243	0.79

time domain features, frequency domain features, and time-frequency domain features. Studies have revealed that the time domain features are generally superior to the frequency domain features due to their lower computational complexity (i.e., no transformation is required) [38]–[40]. Hence in this study, only time-domain features are used for classification. In total 4-time domain features were extracted from every one of the eight channels of the MYO armband. The features used in this paper are Integrated EMG (IEMG), Mean Absolute Value (MAV), Root Mean Square (RMS) and Waveform length (WL) [41]–[43].

C. Feature scaling

Data standardization is one of the pre-processing steps where the data features are transformed to contribute equally to each feature. Data standardization improves the model's performance and helps in faster convergence of gradient descent [44], [45], hence speeding up the model learning process. In this work, the Z-score Normalization was performed on the raw dataset, which scales the data by setting the mean equal to zero and variance to the unit. The standard score is calculated as follows:

$$z = \frac{(x-u)}{s} \tag{2}$$

where u and s represents the mean and standard deviation of the training sample x.

D. Statistics

All the analyses were done using Python libraries: NumPy, pandas and stats models. A paired t-test was performed for the stroke patients for the real-time performance parameters between the first and the last day of the protocol to assess the statistical significance. A t-test was also performed for the stroke patients for the ID and performance parameters, except throughput because the ID and throughput are dependent quantities and hence, we can't perform a t-test for them.. The coefficient of determination (R^2) between completion time and ID for 2 DOF games was determined in order to investigate the suitability of Fitts' law approach for real-time user performance evaluation. P-values less than 0.05 were considered significant. The results are expressed as mean ± standard deviation.

IV. Rehabilitation Protocol

A. Machine Learning Model

For selecting the machine learning algorithm for real-time evaluation, cross-validation was done, wherein multiple shallow machine learning algorithms (i.e., SVM, Decision Trees, XGBoost, Gradient Boost and CatBoost) were trained offline on the processed data acquired from different intact subjects. Gradient Boost was selected

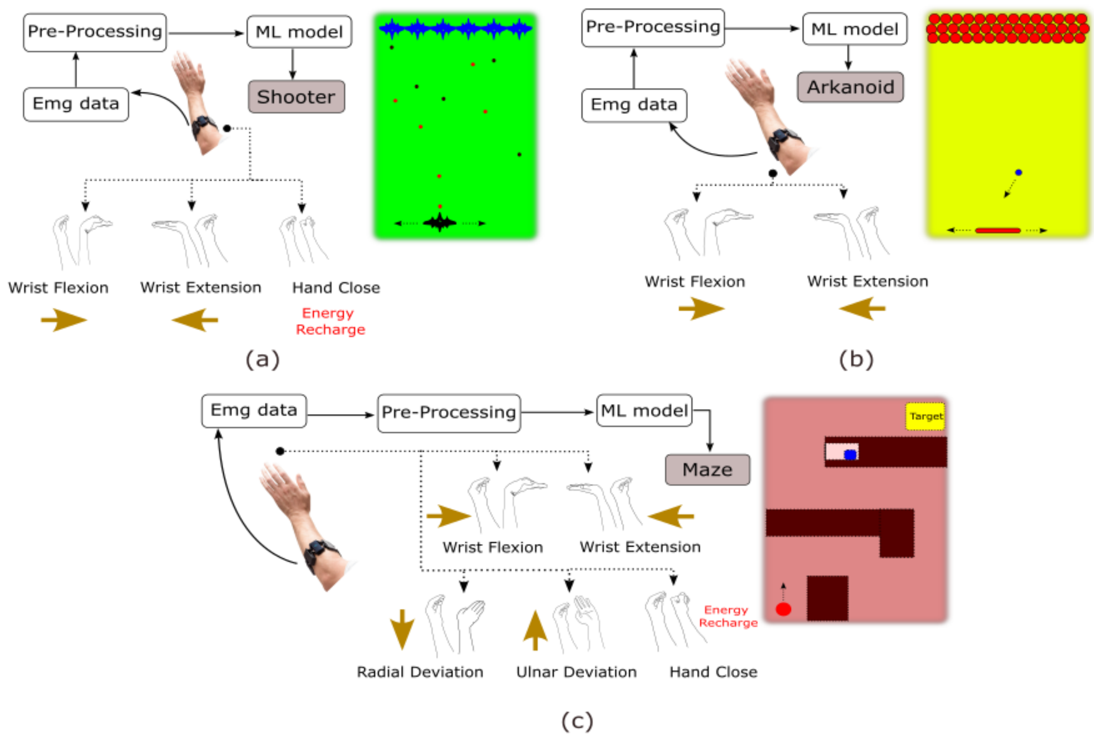

Fig. 4. Summary of games played by subjects (a) Space shooter: wrist flection and extension moves the ship to dodge the incoming bullets and hand close to recharge energy for shooting the enemies overhead (b) Brick breaker: wrist flection and extension moves the paddle to ricochet the incoming ball towards the bricks overhead (c) Maze: wrist extension, wrist flection, wrist radial and ulnar deviation maneuvers the ball around the maze to reach the target, Hand close destroys the bricks and unlocks the path of the key.

as the classification algorithm due to its best performance. The implementation and hyperparameter tuning of all the machine learning models were done in Python, using the scikit-learn framework for machine learning. All the models were trained on a local CPU with 128 GB SSD and 8 GB RAM.

B. 2D Games Experience

In this study, we used Pygame (Python library for 2D game development) to create three 2D games, namely, the Brick breaker, Space shooter, and Maze, each having a different degree of freedom explained in Fig. 4. The games were designed so that they imitate the physical therapy exercises to facilitate the rehabilitation process by evoking positive emotions through a reward system. In the aforementioned games, left, right, up, and down movements are controlled by wrist flexion, wrist extension, wrist radial deviation and wrist ulnar deviation, respectively. Hand close is controlled by the hand close gesture and serves a different purpose in 1 DOF and 3 DOF games. The number of movements in a game is determined by their respective degree of freedom. The left and right movements are reversed for left-handed players and must be corrected beforehand. The gameplay and specific features of each game are elaborated upon in the following sections.

1) Brick-Breaker: The Brick-Breaker is a 1 DOF game that imitates the mechanics of the famous "Arkanoid" video game (developed by Taito corporation). It has two gameplay modes; one is for pure entertainment purposes, while the other records the performance parameters for real-time user performance evaluation as shown in Fig. 3(a) and 3(b). In the first mode, the subject is tasked to move a paddle left and right to deflect the incoming ball into the rows of blocks at the top of the screen. The goal is to destroy all the blocks and eventually clear the screen by ricocheting the incoming ball towards the blocks. An optional guide that shows a red box in which the ball will land can be enabled. The second mode consists of a ball and two paddles, each on top and bottom of the game window. The top paddle sends a ball ten times towards the bottom paddle, which users control via a hand gesture. A red box appears in which the ball will land. The user is tasked to successfully stop the paddle in the middle of the box and wait for the ball to hit the paddle. The box becomes green when the paddle completely overlaps with the paddle. In both gameplay modes, the player has six lives, losing one when the player misses the ball. The game ends when the player loses all lives or destroys all the blocks. The paddle can only move horizontally. Hence, this game uses only two hand gestures (i.e., flexion and extension).

2) Space Shooter: The Space shooter is a 2 DOF game that imitates the mechanics of the arcade game, namely space invaders. It is a fixed shooter video game in which the player moves a laser cannon ship horizontally across the bottom of the screen and shoots at aliens overhead as shown in Fig. 3(c). The enemy ships randomly shoot in hopes of hitting the ship, while the asteroids pinpoint the ship's location and hurl towards it. Using wrist flexion and extension, the player moves the ship horizontally to dodge enemy bullets and asteroids. The player fires at enemy ships and asteroids by filling the energy meter, accomplished by closing the hand when the ship is inside the target box. Thus, only three gestures are used in this interactive game. The objective of the game is to destroy all enemy ships and asteroids while avoiding their attacks.

3) Maze: Maze is a 3 DOF game that is designed from scratch. The player is always located on the bottom left side and is tasked to manoeuvre the ball left, right, up, and down to collect all the rewards in the maze scene. The end goal is to get to the door on the top right side of the game by collecting maximum rewards (i.e., diamonds) located on the map while following the intended path as shown in Fig. 3(d). On the left middle side, two wooden bricks are blocking the path which leads to the key. The player has to position the ball in the grey box and close its hand till the energy bar fills. When the energy bar is filled, wooden boxes are destroyed, and the player can retrieve the key. The retrieved key can be used to open a locked chest and collect the star. The ball's path is drawn as it moves and is saved for evaluation of path efficiency. Thus, five gestures are utilized in this video game.

C. System Description

An MIT-licensed library, "Pyomyo", was used for data acquisition. This library provides three sEMG data acquisition modes; (i) preprocessed data at 50 Hz, (ii) filtered data at 200 Hz, and (iii) raw data at 200 Hz. This study used raw data acquisition mode for sEMG data collection. To avoid lag, game and data acquisition are run on different processors making the game dependent on the data acquired from the serial port. All games are run on 200 frames per second (FPS), constrained by the sampling frequency of the MYO armband. During data acquisition, the MYO connect application receives raw sEMG data from the MYO armband via Bluetooth and sends it to Python code. This data is collected, preprocessed, and fed into a machine-learning algorithm for model training. The trained model is saved as a pickle file that is afterwards retrieved in real-time users' evaluation for drawing inference. This inference is sent to the game, where it is translated into the corresponding game movements shown in Fig. 5.

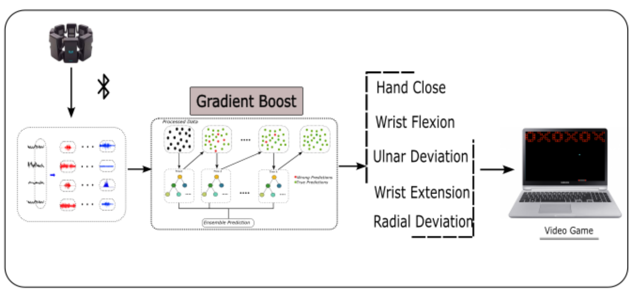

Fig. 5. Proposed Rehabilitation system description

V. Results

A. Offline results

Table III represent the goniometer readings of various movements for stroke patients before and after following the conceived experimental protocol. The stroke patients showed considerable improvements in hand mobility by following the experimental protocol, evidenced by the increase in joint angles (active finger flexion, increased from 0° to 10°) measured for stroke patient two.

B. Conformity with Fitt's Law test

A strong linear relationship was obtained between completion time (s) and index of difficulty ID (bits) across the subjects. This indicates the high compliance of the given study to Fitts' law and affirms the appropriateness of utilizing the Fitt's Law test. The high coefficients of determination R^2 values observed for both healthy ($R^2 \geq 0.98$) and stroke subjects ($R^2 \geq 0.88$) provide strong support for the validity of the proposed rehabilitation protocol for the sEMG-based interactive rehabilitation therapies shown in Fig. 6.

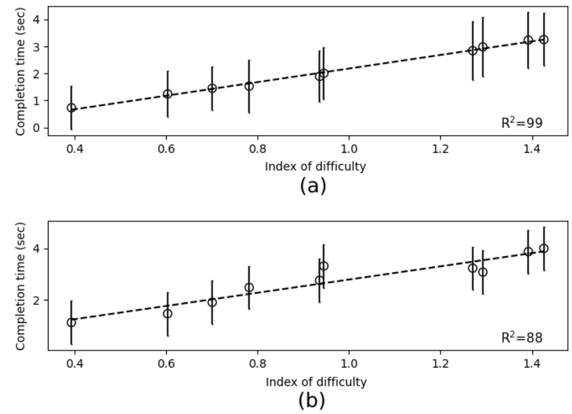

Fig. 6. Correlation between the completion time (CT) and the index of difficulty (ID) for both (a) able-bodied individuals and (b) stroke patients.

C. Real-time Performance parameters

Fig. 7 and 8, summarizes the overall real-time performance parameters for the two-stroke patients. *Brick-Breaker:* Patient 1 had less difficulty in playing this game. Paired t-test showed significant improvement in the average completion rate and score of 5th day when compared to the average completion rate ($t(2) = -6.95, p < 0.05$) and score ($t(2) = -3.78, p < 0.05$) of the 1st day.There was substantial improvement in average throughput (2.5%, p = 0.06) and overshoot (14.5%) of the 5th day as compared to the respective parameters of the 1st day. For Patient 2 in both stages of 1 DOF game: there was considerable improvement between all parameters of the 1st day compared to respective parameters of the 5th day; however, no statistical significance was revealed by a paired t-test. Though further analyses using a simple t-test between the index of difficulty and all real-time performance parameters (except throughput) showed a statistical significance ($p < 0.05$) with a linear decreasing trend with an increase in the index of difficulty. *Space shooter:* Patient 1 faced difficulty in first two days while playing this game. The average completion rate, throughput and overshoot of 5th day showed major improvement when compared to the average completion rate ($t(2) = -4.71, p < 0.05$), throughput ($t(2) = -5.11, p < 0.05$), and overshoot ($t(2) = 4.71, p < 0.05$) of the 1st day. There was no significant improvement found when average completion time of 5th day was compared with completion time ($t(2) = 0.21, p = 0.42$) of 1st day. *Maze:* For stroke patients, paired t-test did not show any improvement in path efficiency of 5th day as compared to path efficiency of 1st day ($t(2) = -1.94, p = 0.096$). Fig. 9 display the path efficiency for the trails performed by a stroke subject in 3 DOF video game. A straight line inside the ideal path would indicate a 100% efficiently performed task, whereas deviations from the ideal path indicate errors shown in Fig. 10.

VI. Discussion

To our best knowledge, this is the only study that has incorporated the Fitts' law based real-time performance parameter into VGT for assessing stroke patient rehabilitation over time. In the last couple of years, extensive efforts have been devoted to the development of standalone rehabilitation systems, requiring the least therapeutic intervention due to the worldwide increase in disability and the inadequate global healthcare sector. For this reason, researchers have conducted a large amount of study for developing interactive rehabilitation protocols for providing home-based rehabilitation. However, most of these studies lack real-time user performance feedback for

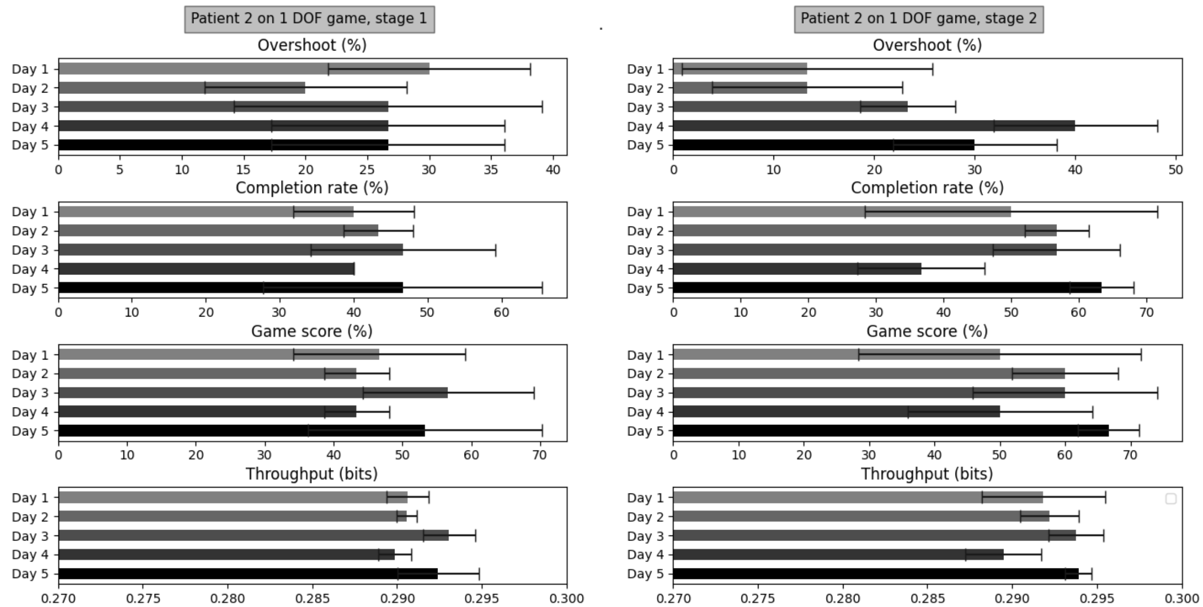

Fig. 7. Realtime performance parameters (Mean ± Std dev.) for stroke patient 2 with parameters averaged over the entire day.

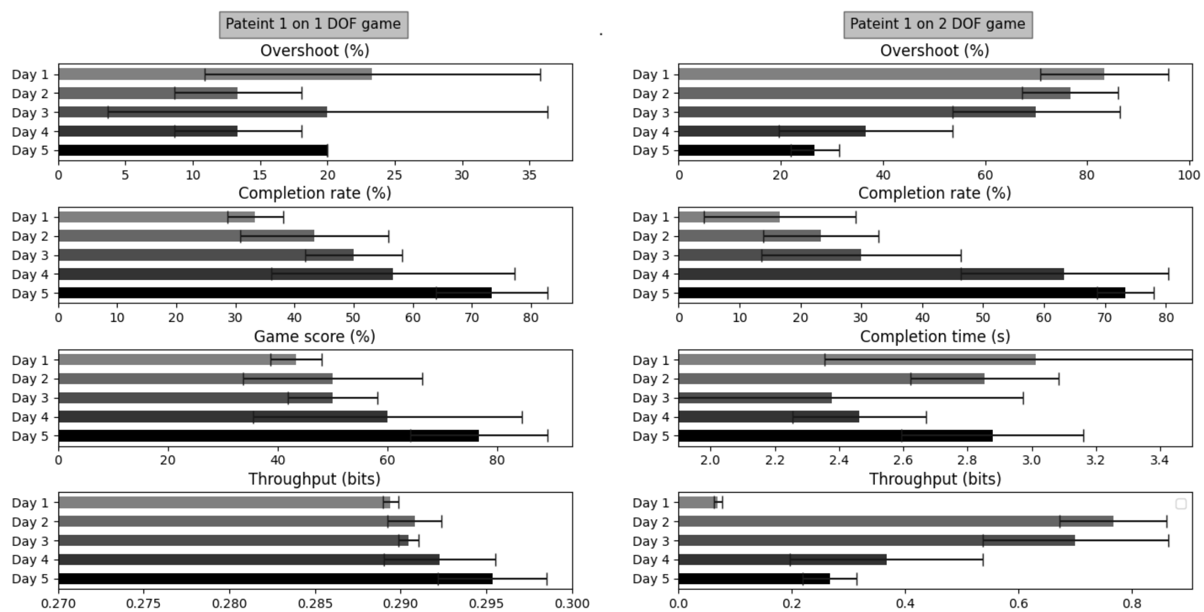

Fig. 8. Realtime performance parameters (Mean ± Std dev.) for stroke patient 1 with parameters averaged over the entire day.

assessing patients' conditions over time [7], [11], [18], [19]. In this study, we evaluated the effectiveness of the proposed rehabilitation protocol over three weeks in the context of real-time user performance feedback using Fitt's law approach. The high R2 values obtained across the subjects from regression plots during the Fitts' Law test confirmed the appropriateness of utilizing the Fitt's Law test.

For the overall performance based on completion rate, score overshoot and throughput, the t-test showed a significant difference between the first and last day of the protocol as shown in Fig. 7 and 8. On average, for the brick breaker game, the completion rate (73.33 ± 11.55) and score (76.67 ± 15.28) on the fifth day were significantly better ($P < 0.05$) when compared to the respective parameters of the first day. Similarly, on average, for the space shooter game, completion rate (73.33 ± 5.77), overshoot (26.67 ± 5.77) and throughput (0.267 ± 0.057) on the fifth day showed significant improvement ($P < 0.05$) when compared to respective parameters of the first day. This indicates an improvement in the range of hand

TABLE III

JOINT ANGLES MEASURED USING GONIOMETER OF STROKE PATIENT 2

Goniometer's readings			
Before Protocol		After Protocol	
Movements	Angle(deg)	Movements	Angle(deg)
Wrist Flexion	30°	Wrist Flexion	30°
Wrist Extension	5°	Wrist Extension	5°
Active Finger Flection	0°	Active Finger Flection	10°
Wrist Radial Deviation	10°	Wrist Radial Deviation	10°
Wrist Ulnar Deviation	0°	Wrist Ulnar Deviation	0°

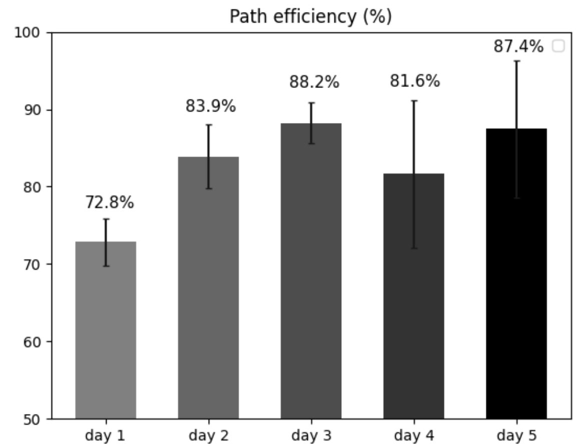

Fig. 9. Path efficiency averaged over the entire day for stroke patient 1 in maze.

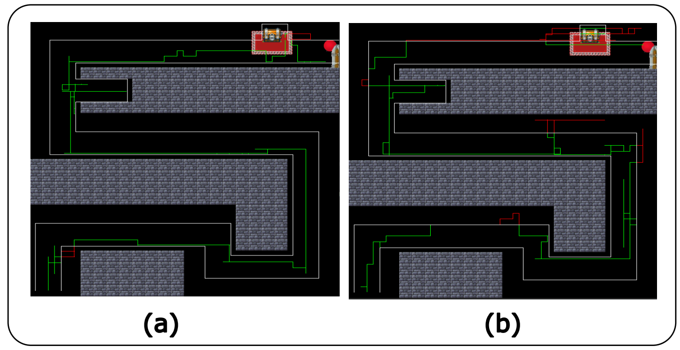

Fig. 10. Visual representation of the (a) best and (b) worst efficient paths taken by patient 1 in the maze game for the first and last day of experimental protocol.

motion of stroke patients. However, the lack of consistency between inter-day results is quite interesting and indicates the influence of external factors (the effect of cold, spasticity in hand). To counter this effect, a comprehensive study comprising multiple weeks and a large sample size might provide a coherent long-term trend in results. This observation has an important implication on HBR based on VGT, which has the potential of providing interactive, low cost and expeditious therapy, thus making rehabilitation accessible for all. There was an increase of 10° in active finger flexion, which can be attributed to the continuous hand opening and closing in stage 1 of the brick breaker. The high rating of rehabilitation protocol given by stroke patients on post therapy evaluation form indicates no mental workload and discomfort symptoms while undergoing the proposed rehabilitation. On the other hand, many unpleasant symptoms are induced by the use of VR [14], [15], [17]. Future work can be done on developing a standalone rehabilitation system by incorporating an assistive robotics glove into the proposed rehabilitation protocol that will aid stroke patients in gesture performance.

While the results of this study have shown significant improvement in performance parameters for stroke patients, there is still a need to study the proposed techniques on a larger dataset. Further studies need to be done with a large number of participants and a control group in order to determine the effectiveness of the proposed rehabilitation protocol. In this study, we only used sEMG from the myo-arm band and a hand full number of gestures. In future work, we will try to incorporate a gyroscope, acceleration, and a greater number of gestures with more dynamic games. Furthermore, it is essential to conduct additional research and large-scale randomized controlled trials before incorporating such innovative rehabilitation techniques into clinical practice.

VII. Conclusion

In this study, an interactive rehabilitation protocol comprising multiple DOFs game control interfaces was developed for stroke patients with upper limb impairment. The games were designed to imitate the physical therapy exercises for facilitating the rehabilitation process by evoking positive emotions through a reward mechanism. A three-weeklong protocol was followed using ten able-bodied subjects and two stroke patients for assessing the usability of the proposed rehabilitation protocol using the Fitts' Law approach. From the overall performance based on offline results, stroke patients showed considerable restoration in their hand mobility. Moreover, the significant improvements in the real-time performance of stroke patients imply that the proposed VGT has great potential to be employed in interactive HBR techniques. However, further investigation is required to determine the useability of the proposed rehabilitation protocol in a clinical environment.

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