Adaptive Robotic Rehabilitation using Muscle Fatigue as a Trigger

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ABSTRACT

Fatigue is a pervasive symptom following brain injury or disease. It has been known to impact recovery and hence is an important factor in rehabilitation. Robotic rehabilitation may be one way to reduce fatigue because of the robot's capability to adapt to user's performance. This paper explores an adaptive rehabilitation system to provide personalized upper limb rehabilitation. The system collects EMG data from the major muscles responsible for movement and adapts the forces used for rehabilitation (assistive and resistive) in real time based on muscle fatigue. Experimental results and the user survey outcomes show that the system was able to detect the onset of fatigue within ± 10 seconds error margin. Overall, it was found that the subjects experienced lower fatigue and had a higher probability of compliance and engagement with the proposed robotic rehabilitation system.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; *Interaction design*; • **Applied computing** → **Life and medical sciences**; • **Computer systems organization** → Real-time systems;

KEYWORDS

Human-Computer Interaction, Assistive Robots, Robotic Rehabilitation, Personalized Rehabilitation, Fatigue, EMG, Signal Processing and Adaptive Forces

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1 INTRODUCTION

Accidents or other physiological or neurological conditions can severely affect the motor functions, and thus prevent people from performing simple daily life activities such as brushing teeth, holding a glass of water, tying shoes, etc. These cases may include stroke, multiple sclerosis (MS), shoulder dislocation and traumatic brain injury (TBI), among others. According to an estimate in 2012 [26], approximately 795,000 people suffered from a stroke in the United States. Another estimate puts the prevalence of MS at 149.2 per 100,000 people in 2012 [9]. Fortunately, some of these disabilities are not always permanent and in some cases, they can be improved through physical rehabilitation. Physical rehabilitation requires the repetition of exercises over a long period of time, which has been shown to improve motor function.

In conventional rehabilitation, the patients are evaluated by a therapist in a rehabilitation center. While conventional rehabilitation may be effective, it is also labor intensive. In addition, it is often not enjoyable and can be inconvenient to patients needing to travel a long distance to reach the rehabilitation center. In recent years, research efforts in robotic rehabilitation and gamified rehabilitation [6, 13] have shown promise in overcoming these obstacles, by making rehabilitation user-centered and adaptive to the patient's needs. Gamified rehabilitation and robotic rehabilitation can use a virtual reality environment to engage patients and guide exercise during rehabilitation [4]. Studies have shown that when the patient is engaged during rehabilitation, they have a better chance of retaining the white matter integrity in their brain [3].

Robots are particularly amenable to providing personalized rehabilitation therapy, as they are specifically designed to do repetitive tasks and collect large amounts of data with the sensors that are embedded in them. There are many different types of robots used in health care applications such as surgical robots, socially assistive robots and rehabilitation robots, among others. Surgical robots are used to perform precise operations as well as remote surgeries [25]. Socially assistive robots are commonly used to assess and train

the patient's cognitive abilities without physical contact [24] by communicating with patients through sound and/or expressions (e.g. facial expressions).

Rehabilitation robots are designed to assist the patients to perform physical exercises that help regain the use of motor functions. Some examples of rehabilitation robots are robotic arms, exoskeleton robots and movement therapy robots, among others. Lum *et al.* [22] used a 6-degrees of freedom (DOF) robot manipulator to provide upper-limb physical rehabilitation to post-stroke patients and compare it to conventional therapy techniques. Their results indicate that patients who performed the robot-assisted rehabilitation had significantly greater improvement in strength, reach and an overall decreased impairment, in the first two months. Beer *et al.* [1] used an exoskeleton robot with a treadmill to perform gait rehabilitation on patients with MS. Their findings show that robot-assisted gait training was effective, and can significantly improve walking distance, velocity and knee-extensor strength of patients with severe walking disabilities.

Fatigue is a complex and subjective phenomenon that does not have a single definition that is unanimously accepted [34]. It has been studied in various disciplines, including neurology, nursing science, psychology, and medicine. One definition of fatigue by Jensen *et al.* [14] is:

"Acute fatigue is most often caused by excessive physical or mental exertion and can be relieved by rest. Normative fatigue may be influenced by circadian rhythm and results from the activities of daily living, while chronic fatigue is most often prolonged by stress or tension on the body and is less likely to be relieved by rest alone."

This paper focuses on acute muscular fatigue.

There are two main ways of detecting fatigue, subjective which depends on self-reporting, and objective which measures a person's physiological and/or cognitive performance based on collected sensor data. The most common way of measuring subjective fatigue involves the subjects taking a survey where they answer questions based on their experience or feelings. The survey would then extract the level of fatigue through the given answers. Some of these methods include the Chalder Fatigue Scale (CFS) [5], Krupp's Fatigue Severity Scale (FSS) [18], the Modified Fatigue Impact Scale (MFIS) [33] and the Visual Analogue Scale (VAS) [19]. Objective measures of fatigue have also been studied. Analyzing Electromyography (EMG) parameters like mean and median frequencies have been successful in detecting physical fatigue [7, 8]. Other measures like EEG, heart rate variability and blood biomarkers have been used to detect fatigue while driving [28].

The fact that rehabilitation exercises repetitively exercise the muscles frequently lead to physical fatigue. This type of muscle fatigue could have a negative impact on the patient's performance and the effectiveness of therapy. It may also lead to patients compensating for their fatigue by altering their stance and movements, which may result in soreness and long-term musculoskeletal issues [29]. Therefore, it is important to understand and account for physical fatigue during rehabilitation.

Robotic rehabilitation provides one way to adjust rehabilitation exercises in real time to reduce physical fatigue through changing the forces exerted by the robot. A study conducted by Mugnosso

et al. studied the fatigue experienced by subjects while using a robotic manipulandum [27]. They analyzed EMG data to detect muscle fatigue. Another study conducted by Octavia *et al.* aimed to analyze muscle fatigue in persons with MS [29]. EMG signals during robot-assisted tasks were analyzed here as well. Fatigue detection from EMG signals has also been used in human-robot co-manipulation tasks [30]. Here the robot is part of an adaptive system, where it learns the subject's physical limitations or skills from human demonstration. When fatigue is detected, the robot uses the learned skills to complete the physical part of the task, thus reducing the physical workload on the subject and allowing him/her to recover. Apart from EMG, a subject's performance and force output have also been used to determine muscle fatigue. Huq *et al.* [12] created a fuzzy logic based system that monitored physical fatigue using these parameters and provided adaptive forces to the patient during rehabilitation.

This paper introduces a system for adaptive upper-limb rehabilitation. Here the adaptive element of the system is the resistive and assistive forces applied to the subject. The adaptive element is triggered by muscle fatigue measured using EMG. The main contribution of this paper is a system that challenges patients during rehabilitation but is also sensitive to their physical limitations and provides assistance when needed.

The rest of the paper is organized as follows. Section 2 gives an overview of the experimental procedure, including the physical exercises used as rehabilitation tasks, a preliminary study, and the system architecture. Section 3 covers data collection, data analysis and user surveys. Section 4 discusses the results and the future work, and the conclusion is summarized in Section 5.

2 EXPERIMENTAL PROCEDURE

2.1 Exercises

There are multiple exercises that are used for upper-limb rehabilitation. Among them, three common exercises were considered; Shoulder Flexion, Shoulder Abduction and Elbow Extension [10, 11, 15]. All three exercises were performed while sitting upright on a stool as shown in Figure 1. For Shoulder Flexion (SF), the subject held their arm straight in front of them and raised it to the overhead level. During Shoulder Abduction (SA), the subject held out their arm to the side and raised it by their side to the shoulder level. For Elbow Extension (EE), the subject held their arm to their side with their elbow behind them, then, leaned forward and extended their arm backward.

During the exercises, EMG data was recorded from the major muscle responsible for the movement. This was done to reduce the number of sensors attached to the subject and to decrease the complexity of computation. Data from their deltoids was recorded during SF and SA [16, 21], while data from their triceps was recorded during EE [17]. During these exercises, the subjects were asked to move the end effector to the final position and hold it there. This created isometric contractions in their muscles. An isometric contraction is when the load on the muscle increases while the muscle length and joint angle remain the same [31].

Figure 1: A- Shoulder Flexion (SF) B- Shoulder Abduction (SA) C- Elbow Extension (EE). The green circles indicate the start positions and the red circles indicate the end positions

2.2 Preliminary Study

Two studies were conducted in this project, a preliminary study to collect the necessary data to design the fatigue detection algorithm, and an evaluation study to analyze the performance of the system. The evaluation study is explained in detail in Section 3.

In the preliminary study, the data were recorded from 10 healthy subjects. The subjects were asked to perform the three exercises using the Barrett WAM arm (Barrett Technology, Massachusetts, USA) while EMG was recorded from their deltoid and triceps. The subjects started the exercises from the respective start position, and upon instruction moved the end effector to the final position. They were asked to hold this position until they started to feel fatigued. The subjects were instructed to let the researchers know the moment that they started to feel fatigued rather than to wait until they were unable to maintain the position of effector. This was a subjective measure of fatigue which was used as the ground truth. When subjects indicated that they felt fatigued, the researcher conducting the experiment marked the time point on the computer, and the subjects lowered their arm. This time point was the temporal location of the subjective fatigue and was used in conjunction with the EMG data to design the fatigue detection algorithm.

Figure 2: System Architecture

2.3 System Architecture

The robotic rehabilitation system was designed with two main devices; Delsys Trigno Wireless EMG Sensor (Delsys Incorporated, Massachusetts, USA) and Barrett WAM arm. Delsys EMG sensor was used to collect EMG recordings from the muscles while performing the exercises. As mentioned before, for SF and SA the EMG data was collected from the deltoid, and for EE the data was collected from the triceps. The Barrett WAM arm was used to perform the exercises. The arm is a 4-DOF robot with a spherical handle, which the subjects held, as the end effector. The Barrett robot can provide forces that are similar to forces experienced while holding weights during rehabilitation. The robot also restricts the subject's movement to a particular path and this path can be changed to facilitate different exercises. Section 2.3.4 explains more about path control before starting the experiment. This feature enabled the system to be used by different people as they may have different arm trajectories. Moreover, this feature also allows the system to be used for different types of exercises that were not included in the study.

The system consists of four parts; Data Acquisition, Fatigue Detection, Robot Control, and Exercise Path Control. Figure 2 shows an overview of the system architecture.

2.3.1 Data Acquisition. EMG data was collected using the Delsys Trigno EMG sensor at a sampling frequency of 2000 Hz. This system has a base unit with which the sensor unit communicates. The data was recorded using a User Interface (UI) designed in LabVIEW (National Instruments, Texas, USA). Figure 3 shows the Data Acquisition and Fatigue Detection UI.

2.3.2 Fatigue Detection. A real-time fatigue detection algorithm was created using LabVIEW. To identify physical fatigue, the median frequency was extracted from raw EMG data. Spectral analysis

Figure 3: Data Acquisition and Fatigue Detection UI. The graphs represent the signals (EMG, Median Frequency and Slope) in real time.

of EMG during fatigue has shown an influence of fatigue on the median frequency [7, 8, 32]. Apart from this, studies have also used mean frequency and Root Mean Square (RMS) to identify fatigue [2]. These methods were analyzed in the preliminary study but were not considered because, in our observation, they had a higher noise level. Muscular fatigue affects the conduction velocity of the muscle fiber, which is defined as the speed at which the entire muscle fiber depolarizes. Change in the conduction velocity has an effect on the frequency scale of the EMG from the muscle. The median frequency can be an indicator of this change [23].

To detect fatigue, a drop in the median frequency was needed. In our study, the median frequency was calculated over a window of 0.125 seconds. To avoid noise in the median frequency signal, the slope was calculated over a window of 5 samples (0.625 seconds) by fitting a linear line over the median frequency data. A decrease in the slope value indicates a drop in the median frequency. To identify fatigue, a window of 40 samples (5 seconds) was considered. If within these 40 samples, there is no slope value greater than the first point in the window, the system considered it as the onset of fatigue. If within that window a greater slope value existed, then the window restarted with the new high point. The sizes for these windows were optimized using the preliminary study data. Figure 4 illustrates the steps for processing raw EMG data, median frequency, and the slope of median frequency.

2.3.3 Robot Control. The Barrett WAM arm was used to perform the rehabilitation exercises. As described in [20], a custom program to control the robotic arm during the exercises was designed using the LibBarrett library. This control system was capable of providing forces to the subject. These forces were used to perform adaptive rehabilitation exercises.

The system was capable of providing forces in both resistive and assistive mode. During each exercise, two positions were important; the starting position and the ending position. Resistive forces were defined as the forces applied to keep the end effector at the start position while the subject tries to move it to the end position.

Assistive forces were defined as the forces applied to help the user move the end effector from the start position to the end position. At the start of the exercise, the system provided resistive forces to the user. While performing the exercise, the fatigue detection algorithm analyzed the EMG data and determined physical fatigue. Once fatigue was detected, the algorithm instructed the control system to provide assistive forces, which were capped at 20N.

2.3.4 Exercise Path Control. A front end UI program (Exercise Path Control UI) was created to design the exercise paths. Figure 5 shows the front end of the UI which would be presented to a therapist in a clinical setting. It is based on the UI discussed in [20] and is intended to be used by the therapist to set up the exercise protocols. The UI was designed in Unity and consisted of a sphere which represented the end effector. This sphere moved in 3D space with the end effector and was used to monitor the exercise. The UI also contains buttons that help set the parameters for the exercise protocols (i.e. SF, SA and EE).

At the start of the rehabilitation session, the therapist uses the Exercise Path Control UI and decides on the exercise protocol. This is done by asking the subject to move the end effector of the robot and the Robot Control system records and stores the path. After this, the therapist starts the rehabilitation protocol and the control system brings the end effector to the start position and restricts the path of the end effector to the haptic path recorded. This, in turn, restricts the path that the subject’s hand could move in. The therapist then increases the resistive forces and adjusts it to the comfort of the subject. This instructs the Robot Control system to apply suitable resistive forces to the end effector, in turn applying forces to subject’s arm.

Once the path is set, the therapist can start the Fatigue Detection system. This system receives the data from the Data Acquisition system and starts analyzing it. The analysis for fatigue is done only when the subject is near the final position. This is done to reduce the noise due to the arm motion. The Robot Control system lets the fatigue detection system know when the subject is near the final location by analyzing the cartesian coordinates of the end effector. Once fatigue is detected, the Fatigue Detection system instructs the Robot Control system to switch from resistive forces to assistive forces.

3 DATA COLLECTION AND ANALYSIS

In this phase, an evaluation study was conducted with 15 male and 5 female subjects with a mean age of 25.65. 18 subjects were right-handed and 2 were left-handed. The study was performed on their non-dominant arm to induce fatigue in a short span of time. This study was overseen by a researcher taking the role of a therapist.

The subjects performed the three exercises using two systems; System 1 and System 2. System 2 consisted of the rehabilitation protocol performed with the robotic arm and fatigue was detected using the EMG sensor. This system consisted of the adaptive element which was triggered when fatigue was detected. System 1 consisted of all the elements of System 2, except the adaptive element. Although fatigue was detected; it was not used to trigger the adaptive element. It was instead used to analyze the temporal error between the system recognizing fatigue and the subject’s

Figure 4: Fatigue Detection - Step 1 is the collection of the raw data. Step 2 is the extraction of the median frequency from the raw data. Step 3 is the extraction of the slope of the median frequency and detecting fatigue

Figure 5: Exercise Path Control UI used by the therapist. The sphere in the bottom left represents the end effector of the robot. The buttons are used to set the exercise protocol.

perception of this fatigue, as described in Section 3.1. The subjects performed the exercise on both systems, and the system order was randomized to reduce order effect.

At the beginning of the study, the subjects signed an informed consent form and were shown a video explaining the study as well as a demonstration of all three exercises¹. This also provided some time for them to relax and remove the effect of physical stress they may have experienced before coming to the experiment. The subjects were not told about the adaptive element, neither were they informed about the differences between the two systems, so as to minimize demand characteristics. As a safety measure, they were instructed to inform the researchers if they felt uncomfortable with the forces applied so that the experiment could be stopped immediately.

The subjects then performed all three exercises, SF, SA and then EE, in succession on one of the systems and then on the other system. At first, the subjects recorded the path for the exercise, then the researchers added resistive forces and adjusted it to the subject's comfort. Similar to the assistive forces, the resistive forces were also

capped at 20N. The subjects were instructed to perform the exercise until they started feeling fatigued. Once they did, the subjects were instructed to keep holding the end effector at the final location for 30 more seconds. This was done to effectively compare between the two systems as during this period they provide different kinds of forces (resistive vs. assistive). The time points of the subjective fatigue and the system detected objective fatigue were recorded. After each exercise, subjects were asked to relax for some time to minimize the cascading effect of fatigue. During this period they were also asked to fill out a survey about their experience.

3.1 Data Analysis

To analyze the validity of the fatigue detection algorithm, the accuracy of detection was analyzed. To this end, two time-points were considered; time of subjective fatigue and the time when the system detected fatigue. For the system to be accurate, these two time-points should be similar. To check this an Equivalence Test, Paired Two One-Sided Tests (TOST), was performed. This test looks for equivalence between two datasets by analyzing the differences between their means and checking whether they lie within a threshold. To do this, two tests are performed, one checks if the differences in the mean are lower than the higher threshold and the other checks if the differences in the mean are higher than the lower threshold. Based on the performance data, the threshold was found to be ± 10 seconds. The differences in the mean were calculated as $M_{\text{System Detection}} - M_{\text{Subjective Fatigue}}$. The upper threshold signifies a delay in detection and lower threshold signifies early detection. In rehabilitation, late detection of fatigue may result in a potentially unsafe situation and therefore is important. Along with this, Mean Absolute Error was also calculated to give an insight into the error without its direction. It was calculated as the mean absolute error between the temporal location of the subjective fatigue and the system detection. Table 1 illustrates the results.

As seen in Table 1, the p-value for the upper threshold (<0.001) and the lower threshold (0.008) for SF were significant. This indicates that the difference between the temporal location of subjective fatigue and system detected fatigue significantly lies within ± 10 seconds. The mean absolute error for SF was 9.444 seconds.

When looking at SA and EE individually the test does not yield significant results. For SA, the lower p-value (<0.001) is significant

¹<https://youtu.be/bYiix8KGqYs>

Table 1: Temporal Analysis

Exercise	P Value Upper	P Value Lower	Mean Absolute Error (s)
SF	<0.001*	0.008*	9.444 ± 7.803
SA	0.16	<0.001*	12.646 ± 9.293
EE	0.709	<0.001*	15.311 ± 9.134

* = P Value < 0.05

but the upper (0.16) is not. This signifies that the difference of the mean may be greater than -10 seconds but could also be greater than +10 seconds. In turn, this indicates that the system could statistically have a delay of greater than 10 seconds. This result can be observed in EE as well, where the p-value for the lower threshold is significant (<0.001) but the upper is not (0.709). The mean absolute error for SA and EE are 12.646 and 15.311 seconds respectively.

The average time for subjective fatigue was also recorded in System 1 and analyzed. The subjects felt fatigue while performing SF, SA, and EE, on an average, after 24.59, 17.89 and 16.76 seconds, respectively. One-way ANOVA test was used to find if the subjective fatigue time points were significantly different among the three exercises. The results from the one-way ANOVA were significant, indicating that the time points from the three exercises were different. Post hoc analysis indicated that there was a significant difference ($P < 0.05$) between SF and EE, but there was no significant difference between any other pair of exercises.

3.2 User Survey

After each exercise, the subjects completed a survey. The survey involved questions on the Likert scale and VAS. These questions were about the subjects' experience regarding the difficulty of the exercise, the fatigue level at the end of the exercise and whether they would perform the exercise again. After completing the exercises using both systems, the subjects were asked about which system they preferred.

Figure 6: Survey Q1: Difficulty Feedback

Figure 6 illustrates the subject's difficulty feedback for all three exercises. The question asked was on a Likert scale, which ranged from 'Very Easy' (1) to 'Very Difficult' (5). The figure shows the subjects' experience. In both systems, the average feedback was between 'Easy' and 'Neutral' for SF and SA; however, the subjects found System 2 to be easier. For EE the average feedback was between 'Neutral' and 'Difficult', but like the previous exercises, the subjects still found System 2 to be easier.

Figure 7: Survey Q2: Fatigue Level

Figure 7 illustrates the subjective fatigue level of the subjects after the exercises. To assess this, the subjects rated their fatigue level on a VAS which ranged from 0-10. On average, when the subjects used System 2, they reported a lower fatigue level than with System 1, for all three exercises. The results also show that the subjects experienced lower fatigue during SF than with the other two exercises.

Figure 8: Survey Q3: Likely to Perform the Exercise again

Figure 8 highlights the subject's likelihood to perform the exercise again with the given system. This was done to measure probable future compliance for the system and exercise. This too was measured on a Likert scale which ranged from 'Definitely Yes' (1) to 'Definitely No' (5). For SF and SA, the average results were between 'Definitely Yes' and 'Neutral', and for EE it was between 'Yes' and 'Neutral'. For all three exercises, the probable future compliance was higher in System 2.

Figure 9: Survey Q4: Preference Feedback

Paired T-Test was used to compare the subjects' answers between System 1 and System 2. When the answers for all three exercises were combined, the differences between the systems were significant for questions 1 ($P = 0.011$), 2 ($P < 0.001$) and 3 ($P = 0.006$). At the end of the study, the subjects were asked about their preference

between the systems. Figure 9 demonstrates the distribution of this preference. 70% of the subjects preferred System 2, while 15% preferred System 1. The rest 15% did not have a preference between the two systems.

4 DISCUSSION AND FUTURE WORK

Fatigue is a complex phenomenon that is defined differently in different fields. It is also very subjective and many of the fatigue detection methods depend on the subject's self-reported fatigue level. There are many studies that try to quantify fatigue, but validating fatigue accuracy is challenging. This paper works to validate the accuracy of the presented fatigue detection algorithm by analyzing the temporal error with respect to subjective fatigue. Here fatigue is studied for rehabilitation purposes, where forces exerted in the rehabilitation are mild to moderate. The fatigue detection algorithm requires a window of 40 samples totaling 5 seconds to confirm the presence of fatigue. This is needed to identify the pattern in the signal.

As seen from the temporal analysis of subjective fatigue and system detected fatigue in SF the system was statistically able to detect fatigue within an error margin of ± 10 seconds. Analysis of SA and EE revealed that statistically, the system may have a delay of more than 10 seconds. However, the same analysis indicated that the system did not have early detection issues. This discrepancy could be explained by the sample size. The sample size of each exercise was 20. Therefore, the power of the individual tests was lower. Another factor could be the exercise difficulty. SF was considered the least difficult of the three exercises, and it was observed that the subjects were able to perform it for a longer time before feeling fatigued.

The survey questions were designed to extract fatigue levels during the exercises and to get a general overview of the subjects' preference between System 1 and System 2. The results from the survey indicated that the subjects preferred the adaptive system over the non-adaptive one. There was a significant difference in the subjects' response to the questions on System 1 and System 2. Overall, the subjects found the exercises easier to perform using System 2 and it yielded a significantly lower fatigue level. This may prevent the subjects from getting exhausted and giving up easily, in turn allowing them to perform more repetitions of the exercise. One important observation was that the subjects found SF significantly easier to perform than EE. Along with this, the fatigue levels reported by the subjects were lower. When the subjective fatigue time points were analyzed, it was found that the subjects were able to perform the SF for a significantly longer period of time than EE. This might indicate that the difficulty of the exercise should be considered while designing robotic rehabilitation protocols. Furthermore, subjects' preference and future probable compliance towards System 2 confirms our initial hypothesis that adding a fatigue based adaptive element can improve subjects' overall experience. This could lead them to perform rehabilitation for longer periods and have a faster recovery.

In the future, we would like to extend this work and design a framework that combines physical and cognitive rehabilitation and can adapt to both subject's physical and cognitive needs. Other works [6] integrated gamification, cognitive rehabilitation, and

physical rehabilitation into a single system. The system used the performance data and physiological data to evaluate subjects' cognitive and physical abilities. Others have designed a system that adapts to user's cognitive abilities [35, 36]. Along with this, we would also like to improve our detection algorithm by using deep learning methodologies.

5 CONCLUSION

This paper introduced a system for adaptive upper limb rehabilitation. The system used muscular fatigue to provide the adaptive element, and it was evaluated by conducting a study on healthy participants. From this study, it was observed that the system was capable of detecting fatigue within an error margin of ± 10 seconds. Moreover, it was found that the subjective level of fatigue was lower in the adaptive rehabilitation system than the non-adaptive system. A survey conducted indicated the subjects' high preference for this adaptive system, and it also indicated a higher future probable compliance of the subjects. Therefore, this demonstrates the validity of using adaptive robotic rehabilitation triggered by muscle fatigue.

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REFERENCES

- [1] S Beer, B Aschbacher, D Manoglou, E Gamper, J Kool, and J Kesselring. 2008. Robot-assisted gait training in multiple sclerosis: a pilot randomized trial. *Multiple Sclerosis Journal* 14, 2 (2008), 231–236.
- [2] M Bilodeau, S Schindler-Ivens, DM Williams, R Chandran, and SS Sharma. 2003. EMG frequency content changes with increasing force and during fatigue in the quadriceps femoris muscle of men and women. *Journal of Electromyography and Kinesiology* 13, 1 (2003), 83–92.
- [3] Laura Bonzano, Andrea Tacchino, Giampaolo Brichetto, Luca Roccatagliata, Adriano Dessypris, Paola Feraco, Maria L Lopes De Carvalho, Mario A Battaglia, Giovanni L Mancardi, and Marco Bove. 2014. Upper limb motor rehabilitation impacts white matter microstructure in multiple sclerosis. *Neuroimage* 90 (2014), 107–116.
- [4] Karin Brüttsch, Tabea Schuler, Alexander Koenig, Lukas Zimmerli, Susan Mérellat, Lars Lünenburger, Robert Riener, Lutz Jäncke, and Andreas Meyer-Heim. 2010. Influence of virtual reality soccer game on walking performance in robotic assisted gait training for children. *Journal of neuroengineering and rehabilitation* 7, 1 (2010), 15.
- [5] Trudie Chalder, G Berelowitz, Teresa Pawlikowska, Louise Watts, S Wessely, D Wright, and EP Wallace. 1993. Development of a fatigue scale. *Journal of psychosomatic research* 37, 2 (1993), 147–153.
- [6] Benjamin Chebaa, Alexandros Lioulemes, Maher Abujelala, Dylan Ebert, Scott Phan, Eric Becker, and Fillia Makedon. 2016. Multimodal analysis of serious games for cognitive and physiological assessment. In *Proceedings of the 9th ACM International Conference on Pervasive Technologies Related to Assistive Environments*. ACM, 30.
- [7] Mario Cifrek, Vladimir Medved, Stanko Tonković, and Saša Ostojić. 2009. Surface EMG based muscle fatigue evaluation in biomechanics. *Clinical Biomechanics* 24, 4 (2009), 327–340.
- [8] PLM Coorevits, LA Danneels, Herman Ramon, Remy Van Audekercke, DC Cambier, and GG Vanderstraeten. 2005. Statistical modelling of fatigue-related electromyographic median frequency characteristics of back and hip muscles during a standardized isometric back extension test. *Journal of Electromyography and Kinesiology* 15, 5 (2005), 444–451.
- [9] Piyameth Dilokthornsakul, Robert J Valuck, Kavita V Nair, John R Corboy, Richard R Allen, and Jonathan D Campbell. 2016. Multiple sclerosis prevalence in the United States commercially insured population. *Neurology* (2016), 10–1212.

- [10] Michael D. Ellis, Theresa Sukal-Moulton, and Julius P. A. Dewald. 2009. Progressive Shoulder Abduction Loading is a Crucial Element of Arm Rehabilitation in Chronic Stroke. *Neurorehabilitation and Neural Repair* 23, 8 (2009), 862–869. <https://doi.org/10.1177/1545968309332927> PMID: 19454622. arXiv:<https://doi.org/10.1177/1545968309332927>
- [11] Murielle Grangeon, Aymeric Guillot, Pierre-Olivier Sancho, Marion Picot, Patrice Revol, Gilles Rode, and Christian Collet. 2010. Rehabilitation of the Elbow Extension With Motor Imagery in a Patient With Quadriplegia After Tendon Transfer. *Archives of Physical Medicine and Rehabilitation* 91, 7 (2010), 1143–1146. <https://doi.org/10.1016/j.apmr.2010.04.011>
- [12] Rajibul Huq, Rosalie Wang, Elaine Lu, Debbie Hebert, Herve Lacheray, and Alex Mihailidis. 2013. Development of a fuzzy logic based intelligent system for autonomous guidance of post-stroke rehabilitation exercise. In *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*. IEEE, 1–8.
- [13] Ekaterina Ivanova, Jörg Krüger, Robert Steingraber, Simone Schmid, Henning Schmidt, and Stefan Hesse. 2015. Design and concept of a haptic robotic telerehabilitation system for upper limb movement training after stroke. In *Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on*. IEEE, 666–671.
- [14] Susan Jensen and Barbara A Given. 1991. Fatigue affecting family caregivers of cancer patients. *Cancer Nursing* 14, 4 (1991), 181–187.
- [15] Sung-Kwang Ju and Won-Gyu Yoo. 2015. Electromyography activity of the deltoid muscle of the weight-bearing side during shoulder flexion in various weight-bearing positions. *Journal of physical therapy science* 27, 10 (October 2015), 3285–3286. <https://doi.org/10.1589/jpts.27.3285>
- [16] Sung-kwang Ju and Won-gyu Yoo. 2015. Electromyography activity of the deltoid muscle of the weight-bearing side during shoulder flexion in various weight-bearing positions. *Journal of physical therapy science* 27, 10 (2015), 3285–3286.
- [17] Erica Kholinne, Rizki Fajar Zulkarnain, Yu Cheng Sun, SungJoon Lim, Jae-Myeung Chun, and In-Ho Jeon. 2018. The different role of each head of the triceps brachii muscle in elbow extension. *Acta orthopaedica et traumatologica turcica* (2018).
- [18] Lauren B Krupp, Nicholas G LaRocca, Joanne Muir-Nash, and Alfred D Steinberg. 1989. The fatigue severity scale: application to patients with multiple sclerosis and systemic lupus erythematosus. *Archives of neurology* 46, 10 (1989), 1121–1123.
- [19] Kathryn A Lee, Gregory Hicks, and German Nino-Murcia. 1991. Validity and reliability of a scale to assess fatigue. *Psychiatry research* 36, 3 (1991), 291–298.
- [20] Alexandros Lioulemes, Michail Theofanidis, Varun Kanal, Konstantinos Tsiakas, Maher Abujelala, Chris Collander, William B Townsend, Angie Boisselle, and Fillia Makedon. 2017. MAGNI Dynamics: A Vision-Based Kinematic and Dynamic Upper-Limb Model for Intelligent Robotic Rehabilitation. *World Academy of Science, Engineering and Technology, International Journal of Medical, Health, Biomedical, Bioengineering and Pharmaceutical Engineering* 11, 4 (2017), 158–167.
- [21] J Liu, RE Hughes, WP Smutz, G Niebur, and K Nan-An. 1997. Roles of deltoid and rotator cuff muscles in shoulder elevation. *Clinical Biomechanics* 12, 1 (1997), 32–38.
- [22] Peter S Lum, Charles G Bugar, Peggy C Shor, Matra Majmundar, and Machiel Van der Loos. 2002. Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke. *Archives of physical medicine and rehabilitation* 83, 7 (2002), 952–959.
- [23] Gazzoni Marco, Botter Alberto, and Vieira Taian. 2017. Surface EMG and muscle fatigue: Multi-Channel approaches to the study of myoelectric manifestations of muscle fatigue. *Physiological measurement* 38, 5 (2017), R27.
- [24] Maja J Matarić, Jon Eriksson, David J Feil-Seifer, and Carolee J Winstein. 2007. Socially assistive robotics for post-stroke rehabilitation. *Journal of NeuroEngineering and Rehabilitation* 4, 1 (2007), 5.
- [25] Ian K McLeod, Patrick C Melder, et al. 2005. Da Vinci robot-assisted excision of a vallecular cyst: A case report. *ENT-Ear, Nose & Throat Journal* (2005).
- [26] Writing Group Members, Véronique L Roger, Alan S Go, Donald M Lloyd-Jones, Emelia J Benjamin, Jarett D Berry, William B Borden, Dawn M Bravata, Shifan Dai, Earl S Ford, et al. 2012. Executive summary: heart disease and stroke statistics—2012 update: a report from the American Heart Association. *Circulation* 125, 1 (2012), 188–197.
- [27] Maddalena Mugnosso, Francesca Marini, Matteo Gillardo, Pietro Morasso, and Jacopo Zenzeri. 2017. A novel method for muscle fatigue assessment during robot-based tracking tasks. In *Rehabilitation Robotics (ICORR), 2017 International Conference on*. IEEE, 84–89.
- [28] Bibhukalyan Prasad Nayak, Sibsambhu Kar, Aurobinda Routray, and Akhaya Kumar Padhi. 2012. A biomedical approach to retrieve information on driver's fatigue by integrating EEG, ECG and blood biomarkers during simulated driving session. In *Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on*. IEEE, 1–6.
- [29] Johanna Renny Octavia, Peter Feys, and Karin Coninx. 2015. Development of activity-related muscle fatigue during robot-mediated upper limb rehabilitation training in persons with multiple sclerosis: a pilot trial. *Multiple sclerosis international* 2015 (2015).
- [30] Luka Peternel, Nikos Tsagarakis, Darwin Caldwell, and Arash Ajoudani. 2018. Robot adaptation to human physical fatigue in human-robot co-manipulation. *Autonomous Robots* (2018), 1–11.
- [31] Dee Unglaub Silverthorn. [n. d.]. *Human physiology: an integrated approach*.
- [32] Foster B Stulen and Carlo J De Luca. 1981. Frequency parameters of the myoelectric signal as a measure of muscle conduction velocity. *IEEE Transactions on Biomedical Engineering* 28, 7 (1981), 515–523.
- [33] N Tellez, J Rio, M Tintore, C Nos, I Galan, and X Montalban. 2005. Does the Modified Fatigue Impact Scale offer a more comprehensive assessment of fatigue in MS? *Multiple Sclerosis Journal* 11, 2 (2005), 198–202.
- [34] Lucas J Tiesinga, Theo WN Dassen, and Ruud JG Halfens. 1996. Fatigue: a summary of the definitions, dimensions, and indicators. *International Journal of Nursing Terminologies and Classifications* 7, 2 (1996), 51–62.
- [35] Konstantinos Tsiakas et al. 2018. *Interactive Learning and Adaptation for Personalized Robot-Assisted Training*. Ph.D. Dissertation.
- [36] Konstantinos Tsiakas, Maher Abujelala, and Fillia Makedon. 2018. Task Engagement as Personalization Feedback for Socially-Assistive Robots and Cognitive Training. *Technologies* 6, 2 (2018), 49.