

Estimating Human Muscular Fatigue in Dynamic Collaborative Robotic Tasks with Learning-Based Models

by

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A Dissertation Submitted to the
Graduate School of Sciences and Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in

Mechanical Engineering



KOÇ ÜNİVERSİTESİ

September 15, 2025

**Estimating Human Muscular Fatigue
in Dynamic Collaborative Robotic Tasks
with Learning-Based Models**

Koç University

Graduate School of Sciences and Engineering

This is to certify that I have examined this copy of a master's thesis by

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and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
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To my family and friends who were there for me when I needed them the most.

ABSTRACT

Estimating Human Muscular Fatigue in Dynamic Collaborative Robotic Tasks with Learning-Based Models

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Assessing human muscle fatigue is critical for optimizing performance in physical human-robot interaction (pHRI) tasks and mitigating safety risks for the human operator. This study presents a data-driven framework for estimating muscle fatigue in dynamic pHRI tasks using surface electromyography (sEMG) sensors attached to the human arm. Subject-specific machine learning (ML) regression models were developed to estimate fatigue levels during cyclic (i.e., repetitive) pHRI tasks. Specifically, Random Forest, XGBoost, and Linear Regression models were trained to estimate the fraction of cycles to fatigue (FCF) using three frequency-domain and one time-domain EMG features. Their performance was benchmarked against a convolutional neural network (CNN) that processes spectrogram representations of filtered EMG signals. Unlike most earlier data-driven approaches that primarily formulated fatigue estimation as a classification problem, our method models the continuous progression of fatigue through regression, enabling tracking of gradual physiological changes rather than discrete states, which is critical for timely intervention and adaptive control in dynamic pHRI tasks. Experiments were conducted with ten participants who interacted with a collaborative robot operated under an admittance controller, performing lateral (left-right) cyclic movements of the end effector until the onset of muscular fatigue. The results demonstrate that the root mean square error (RMSE) of FCF estimation across participants was $20.8 \pm 4.3\%$, $23.3 \pm 3.8\%$, $24.8 \pm 4.5\%$, and $26.9 \pm 6.1\%$ for the CNN, Random Forest, XGBoost, and Linear Regression models, respectively. To examine cross-task generalization in this investigational study, additional experiments were performed with one participant who executed vertical (up-down) and circular repetitive movements. Models trained solely on the lateral-movement data were directly tested on these unseen

tasks. The results indicate that the proposed ML/DL models are robust to variations in movement direction, arm kinematics, and muscle recruitment patterns, while the Linear Regression model performed poorly.



ÖZETÇE

İşbirlikçi Robot ile Yapılan Dinamik Görevlerde İnsan Kas Yorgunluğunun Öğrenme Tabanlı Modellerle Tahmini

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15 Eylül 2025

İnsan kas yorgunluğunun değerlendirilmesi, fiziksel insan-robot etkileşimi (pHRI) görevlerinde performansı optimize etmek ve insan operatörü için güvenlik risklerini azaltmak açısından kritiktir. Bu tez çalışması, insan koluna yerleştirilen yüzey elektromiyografi (sEMG) sensörleri kullanarak dinamik pHRI görevlerinde kas yorgunluğunu tahmin etmek için veri odaklı bir çerçeve sunmaktadır. Kullanıcıya özgü makine öğrenmesi (ML) regresyon modelleri, döngüsel (yani tekrarlı) pHRI görevleri sırasında kullanıcının yorgunluk seviyesini tahmin etmek için geliştirilmiştir. Özellikle, üç adet frekansa bağlı ve bir adet zamana bağlı EMG özelliği kullanarak kas yorgunluğa oluşana kadar kullanıcının yaptığı eforu (FCF) yüzdesel olarak kestirebilmek için Random Forest, XGBoost ve Lineer Regresyon modelleri eğitilmiştir. Bu modellerin performansları, filtrelenmiş EMG sinyallerinin spektrogramlarını girdi olarak kabul eden bir evrişimli sinir ağına (CNN) karşı kıyaslanmıştır. Yorgunluk tahminini bir sınıflandırma problemi olarak formüle eden çoğu önceki veri odaklı yaklaşımdan farklı olarak, yöntemimiz insan eforundaki artışı regresyon yoluyla modelleyerek, dinamik pHRI görevlerinde zamanında müdahale ve uyarlanabilir kontrol için kademeli fizyolojik değişikliklerin izlenmesini mümkün kılar.

Bir admitans kontrolcü vasıtasıyla işbirlikçi bir robot ile etkileşim içinde olan ve kas yorgunluğu oluşana kadar robotun uç efektörü ile yanal yönde tekrarlı sağ-sol hareketleri yapan on katılımcı ile deneyler yapılmıştır. Sonuçlar, katılımcılar genelinde, FCF tahmininin ortalama karesel hatasının (RMSE) CNN, Random Forest, XGBoost ve Lineer Regresyon modelleri için sırasıyla 20.8 ± 4.3 , 23.3 ± 3.8 , 24.8 ± 4.5 ve 26.9 ± 6.1 olduğunu göstermektedir. Bu araştırma çalışmasında, çapraz görev genellemesini incelemek için, dikey (yukarı-aşağı) ve dairesel tekrarlı hareketler gerçekleştiren bir katılımcı ile ek deneyler yapılmıştır. Yalnızca yanal hareket verisi kullanılarak eğitilen modeller, bu görülmemiş görevler üzerinde doğrudan

test edilmiştir. Sonuçlar, önerilen ML/DL modellerinin hareket yönü, kol kinematığı ve kas aktivasyon seviyelerindeki değişimlere karşı kararlı olduğunu, Lineer Regresyon modelinin ise zayıf performans gösterdiğini ortaya çıkarmıştır.



ACKNOWLEDGMENTS

I would like to express my deepest gratitude to all those who have supported and guided me throughout this research journey.

First and foremost, I extend my sincere appreciation to my supervisor, Prof. Çağatay Başdoğan, for his invaluable guidance, expertise, and thoughtful discussions throughout this research. His mentorship has been instrumental in shaping both this work and my development as a researcher.

I am also grateful to Dr. Yusuf Aydin for his insightful feedback and guidance during the early stages of this research.

I would like to also thank my project collaborators, Alireza Sepehr Madani and Pouya Pourakbarian Niaz, who contributed significantly and provided valuable feedback throughout this project. Their discussions, suggestions, and camaraderie made this journey intellectually stimulating and enriching.

Additionally, I would like to express my sincere appreciation to all my other lab mates including Enes Ulaş Dinçer, Sara Hamdan, Berke Ataseven, Berk Güler, Easa AliAbbasi, with whom I shared this research and master's journey, and from whom I learned invaluable lessons.

I acknowledge my entire family for their unconditional love, patience, and unwavering support throughout my academic pursuits. Without their support and that of my extended family, I would never have reached this stage of my life. Their continuous encouragement throughout the years gave me the strength to persevere on this journey.

My sincere appreciation extends to all my friends who provided moral support, celebrated milestones with me, and helped maintain balance in my life during this intensive research period.

I gratefully acknowledge the financial support provided by Koç University through

the graduate fellowship funding program, which made this research possible and allowed me to focus entirely on my studies and research objectives.

Additionally, I would like to thank the Abdulla Al Ghurair Foundation (AGF) for their support and funding during my undergraduate degree, which laid the foundation for my academic journey and enabled me to pursue this advanced research.

Finally, I express my deep gratitude to the friends and colleagues who participated as volunteers in this study. Without their participation and patience during the experiments, this research would not have been possible.



TABLE OF CONTENTS

List of Figures	xii
Abbreviations	xiii
Chapter 1: Introduction	1
Chapter 2: Related Literature	3
Chapter 3: Approach	6
3.1 Hardware Setup	6
3.2 Closed Loop Control Architecture	6
3.3 Experiments	7
3.3.1 Training Experiments	7
3.3.2 Participants	9
3.4 Subjective Rating of Fatigue	10
3.5 Machine Learning	10
3.5.1 Data Processing	10
3.5.2 Modeling	11
3.6 Deep Learning	11
3.7 Cross-Task Generalization	12
Chapter 4: Results	13
4.1 EMG Features	13
4.2 Subjective Rating of Participants	15
4.3 Learning Models	15
4.4 Cross-Task Generalization	16

Chapter 5:	Discussion	19
Chapter 6:	Conclusion	22
Bibliography		24



LIST OF FIGURES

1.1	System Architecture and ML/DL Workflow	2
3.1	Plot of Position, Force, and EMG	8
4.1	EMG Features Plots for Both Channels	14
4.2	FCF vs SRF	15
4.3	Lateral Motion RMSE Results for 10 Subjects	17
4.4	Cross Motion Test RMSE Results	18

ABBREVIATIONS

sEMG	Surface Electromyography
EMG	Electromyography
LD	Lateral Deltoid
PD	Posterior Deltoid
AD	Anterior Deltoid
pHRI	Physical Human–Robot Interaction
OpenSim	A software used for human musculoskeletal system
ODE	Ordinary Differential Equation
GPR	Gaussian Process Regression
DT	Digital Twin
MNF	Mean Power Frequency
MDF	Median Power Frequency
TP	Total Power
RMS	Root Mean Square
MVC	Maximum Voluntary Contraction
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
RMSE	Root Mean Squared Error
FCF	Fraction of Cycles to Fatigue
SRF	Subjective Rating of Fatigue Perceived

Chapter 1

INTRODUCTION

The field of physical human-robot interaction (pHRI) has grown significantly during the last two decades. Since the human is an integral part of pHRI, improving human comfort and ergonomics is important not only for maximizing productivity and efficiency in collaborative tasks [1, 2] but also for reducing safety risks to the human operator [3], including the potential adverse effects of muscle fatigue [4, 5], which can impair performance and increase injury risk over time. Fatigue is a physiological state that takes place after prolonged/accumulated high effort. If the progression of human effort is estimated during a pHRI task, the robot's contribution can be dynamically adjusted to reduce the load on the human and prevent the occurrence of muscle fatigue [6]. For example, in the manufacturing domain, estimating the progression of human effort helps to evaluate the difficulty level of the collaborative task and its sub-tasks to make changes toward reducing potential musculoskeletal injuries. Fatigue estimation is also essential in rehabilitation and sports training to prevent overexertion, tailor exercise intensity, and ensure optimal performance and safe recovery. For example, robotic rehabilitation for post-stroke patients often involves repetitive, rhythmic movements designed to help restore damaged neural pathways [7]. However, the onset of fatigue can interrupt these training sessions and restrict the overall duration of therapy. Therefore, finding a systematic and accurate approach to estimating the progression of human effort towards fatigue is considered to be a knowledge gap in the state-of-the-art.

In some of the earlier pHRI studies, human muscular effort has been indirectly inferred from the force applied by the user, which is typically acquired by a force sensor. Nonetheless, measuring the force alone often does not provide a complete

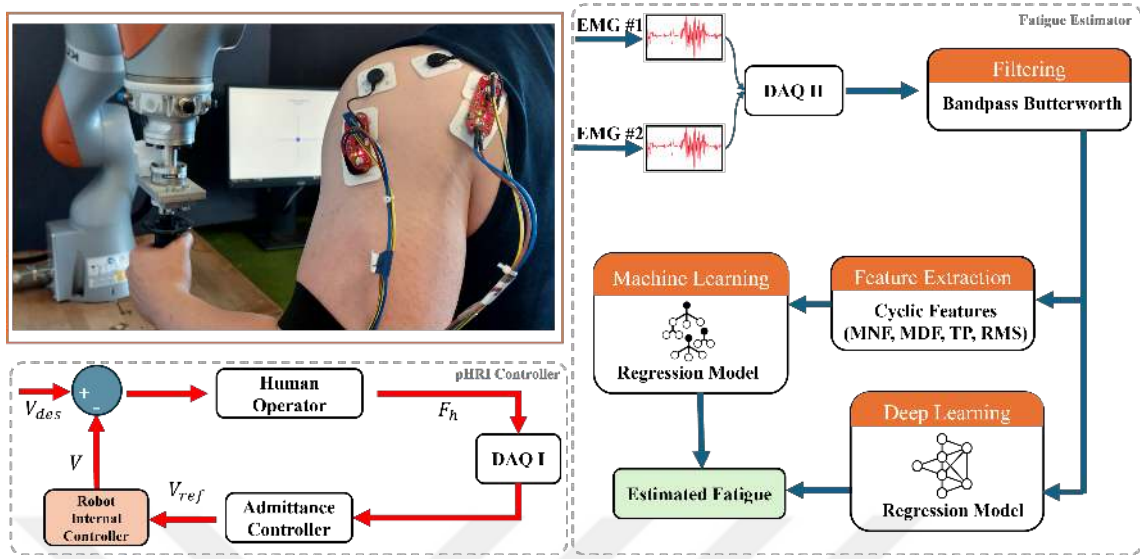


Figure 1.1: Our approach to estimating human muscular fatigue in cyclic pHRI tasks employs learning-based regression models that predict the fraction of cycles to fatigue (FCF) from sEMG measurements.

assessment of human muscular effort in various scenarios. For instance, in collaborative drilling [8, 9, 2] and collaborative surface polishing [5, 10], the magnitude of the normal force applied by the human operator to the workpiece may remain constant, yet muscle fatigue could still occur due to prolonged effort. In both cases, the muscle activation can vary over time due to the dynamic nature of the task. Hence, not just the force applied by the human, but muscular effort should also be assessed by monitoring muscle activity, which is typically achieved by using electromyography (EMG) sensors [5, 8]. EMG sensors detect the electrical signals generated by muscle contractions and can provide information about the intensity and timing of muscle activation. Prolonged efforts in pHRI may lead to a progressive decline in a muscle's ability to sustain performance as observed by the changes in EMG signals, resulting in muscle fatigue, which should be avoided to reduce musculoskeletal injuries and potential disorders.

Chapter 2

RELATED LITERATURE

De Luca[11] identified frequency-based features such as mean power frequency (MNF) and median power frequency (MDF) as reliable metrics for assessing muscle fatigue based on surface EMG measurements. As muscle fatigue occurs, the power spectrum shifts to lower frequencies, and hence, the MNF and MDF decrease gradually. It has also been reported that the RMS amplitude of the EMG signal increases towards the onset of fatigue.

Although these features are effective indicators of fatigue in static loading tasks (as in holding a heavy object in the mid-air) involving isometric muscle contractions, they are less pronounced in dynamic loading tasks (as in repeatedly moving a heavy object up and down), involving isotonic contractions [12, 13]. In a dynamic task, muscles cyclically shorten (concentric phase) and lengthen (eccentric phase) while generating force, promoting intermittent relaxation and improved blood circulation, which helps delay fatigue compared to static loading [14, 15, 13]. Fernando et al. [16] observed that the ratio of MNF to the average rectified value (ARV) provides a more accurate measure of fatigue in dynamic tasks. However, their results were not consistent across subjects. Zahedi et al. [6] relied on the integral of the normalized EMG signal to estimate overall human effort in a dynamic reaching task performed with a robot. They adjusted the robot's damping based on the effort required, ensuring that the subjects did not experience muscle fatigue. Peternel et al. [4] incorporated EMG measurements into a first-degree ordinary differential equation (ODE) to estimate muscle fatigue in a cyclic sawing task performed with a robot. However, this approach does not account for muscle recovery, which was later investigated by Lorenzini et al. [17]. To incorporate the effect of dynamic muscle contractions, including both concentric (shortening) and eccentric (lengthening) actions, of the human arm into the effort estimation, Peternel et al. [18] and

Figueredo et al. [19] employed a musculoskeletal model developed in OpenSim [20], an open-source software platform for modeling, simulating, and analyzing human musculoskeletal system and movement.

More recently, the research in this domain has focused on data-driven machine learning (ML) and deep learning (DL) models for fatigue estimation. Initial studies employing ML models based on EMG measurements primarily targeted the classification of human actions and intent recognition, rather than fatigue [21]. Subsequent efforts have shifted toward DL models, which eliminate the need for manual feature engineering [22]. In the context of fatigue estimation, for example, Karthick et al. [23] evaluated five ML classifiers utilizing 12 EMG features to distinguish between dynamic muscle fatigue and non-fatigue conditions during biceps curl exercises with a 6 kg load. Moniri et al. [24] employed a deep CNN model to simultaneously learn and predict five common EMG features in real time for assessing fatigue in trunk muscles.

Fatigue estimation using EMG-driven ML/DL models has received relatively little attention within the domain of pHRI. In [8], due to the musculoskeletal model's requirement for intensive computations and its limitation to offline operation, a Gaussian Process Regression (GPR) machine learning model was implemented to create a real-time, configuration-dependent mapping from the endpoint force of the robot to the internal muscle forces to estimate human muscular fatigue. You et al. [25] developed a digital twin (DT) framework for real-time fatigue estimation in manufacturing. The DT utilizes a musculoskeletal model developed in OpenSim [20], a bidirectional Long Short-Term Memory (BiLSTM) network, and inverse kinematics to estimate muscle forces first, and then the fatigue based on the ODE model proposed in [18].

In this study, we introduce a learning-based approach to estimate the progression towards human muscular fatigue in pHRI for dynamic and repetitive tasks by analyzing electromyography (EMG) signals acquired from arm muscles (see Fig. 1.1). The contributions of our study are as follows

- We conducted physical human-robot interaction (pHRI) experiments in vir-

tual environments (VEs) using a collaborative robotic arm operated under 3-degree-of-freedom (3-DoF) admittance control. Surface electromyography (EMG) signals were recorded from the arm muscles of ten human participants to train subject-specific ML and DL models for detecting muscular fatigue. The robot’s control loop operated at a high update frequency, enabling real-time haptic rendering of interaction forces during task execution. This real-time force feedback capability within the VE framework facilitated the design and execution of complex pHRI tasks that would be challenging or impractical to implement in physical settings [3], thereby providing a flexible and safe platform for collecting high-quality data for training the learning models.

- Using the learning models, we estimate the fraction of cycles to fatigue (FCF) for cyclic and repetitive pHRI tasks. Previous data-driven ML/DL approaches to fatigue estimation predominantly framed the problem as classification, whereas our approach models the continuous progression of fatigue through regression. This formulation enables tracking of gradual physiological changes rather than discrete states, which is critical for timely intervention and adaptive control in dynamic tasks. We also validate our FCF estimates with the human operator’s self-rating of perceived fatigue for each cycle during the task, which are found to be strongly correlated.
- To enhance the generalizability of our approach across different movement kinematics and muscle groups, the ML regression models were trained using cycle-wise normalized EMG features with respect to the first cycle. The regression performance of the ML models were benchmarked against a DL model trained on spectrogram representations of the EMG signals. Following rigorous training and cross-validation for a single pHRI task, all trained models were evaluated on two additional, distinct pHRI tasks. This cross-task evaluation was designed to assess the robustness and generalization capability of the fatigue estimation framework under different interaction conditions.

Chapter 3

APPROACH

This section introduces our hardware setup for pHRI, our experiments, and the learning pipeline for estimating human muscular fatigue.

3.1 *Hardware Setup*

Our pHRI system is composed of the following major hardware components: a collaborative robot (LBR iiwa 7 R800, KUKA Inc.), a force sensor (Mini45, ATI Inc.) for measuring the human force, and 2 EMG sensors (AT-04-001, MyoWare Inc.) attached to the user's arm for measuring the muscle activation during the execution of the pHRI task.

In our system, the data from the force sensor was sampled at 500 Hz by an internal DAQ card (PCI-6225, National Instruments Inc.) connected to a personal computer. The end-effector position and velocity of the robot are also acquired at the same update rate using the robot's encoders. The EMG data were acquired at 2 kHz by an external DAQ card (USB-6251, National Instruments Inc.) connected to the computer. All software code was developed in the C/C++ and Python programming languages, leveraging multi-threading techniques to enable the seamless acquisition, processing, and integration of multimodal data, including force, robot kinematics, and EMG.

3.2 *Closed Loop Control Architecture*

We employ three decoupled admittance controllers, each dedicated to one of the three Cartesian degrees of freedom (dof), to manage the interactions between the human operator and robot. Our control architecture is shown in Fig. 1.1 (see the lower left corner). In the Laplace domain, the expression for the admittance controller $Y(s)$

can be written as:

$$Y(s) = \frac{V_{\text{ref}}(s)}{F_h(s)} = \frac{1}{ms + b} \quad (3.1)$$

where $V_{\text{ref}}(s)$ represents the corresponding reference velocity in the Laplace domain, which is provided by the admittance controller to be followed by the robot via its internal motion controller. $F_h(s)$ denotes the human force, while m and b represent the admittance mass and damping, respectively. The parameters of the admittance controller for each dof are the same and were carefully selected to maintain the stability of our pHRI system using the analysis approach suggested in [26].

Since the control loop ran at 500 Hz, our pHRI system could display real-time haptic feedback to users during the simulated tasks performed in the virtual environment as well as the tasks performed in the physical world.

3.3 Experiments

3.3.1 Training Experiments

The goal of the primary experiments is to collect data for training our learning models to estimate FCF. Participants were asked to hold the handle of the robot at the level of their umbilicus along the body's midline and repetitively perform translational left-right movements along the X axis (called lateral movements in the text) as shown in Fig. 3.1. In each cycle of the movement, they moved the handle 20 cm to the left of the midline first, then 20 cm to the right of the midline, and finally back to the midline again. The admittance controller in the Y direction was disabled to constrain the robot's motion to the XZ plane (frontal plane) only.

In each trial, participants were asked to follow a visual cursor making cyclic movements at 0.1 Hz on a computer monitor. The experiments were performed under two different admittance damping ($b = 275, 300$ kg/s) to introduce variability to the data while the admittance mass was kept constant ($m = 10$ kg).

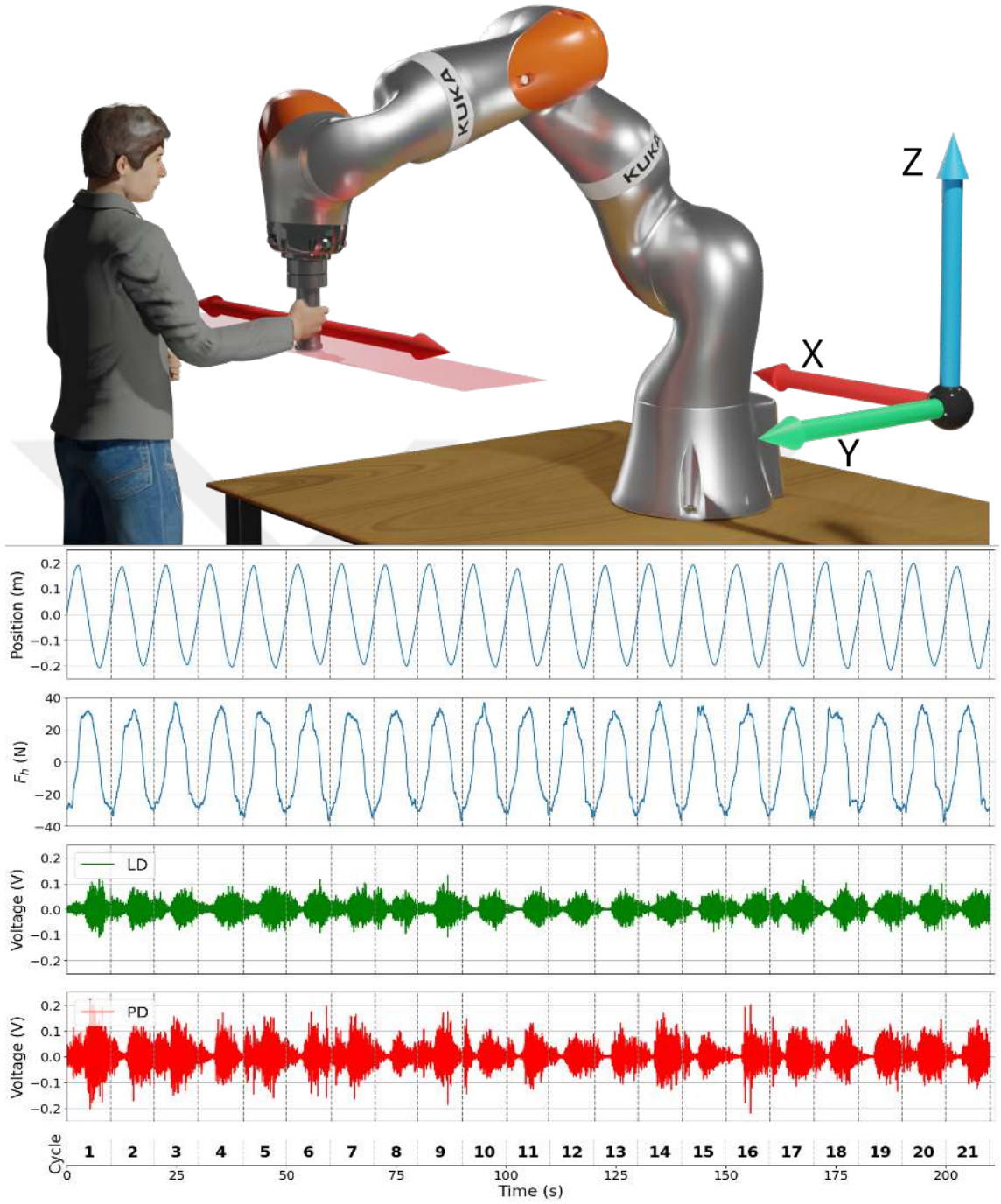


Figure 3.1: The participants of our pHRI experiments were asked to perform cyclic and continuous movements along the X-axis. The end-effector position (first row), human force (second row), and surface EMG signals recorded from the LD (third row) and PD (fourth row) muscles until the onset of fatigue for a representative participant. The vertical dotted lines in the plots are used to separate the cycles.

Before the experiments, participants underwent preparation for EMG electrode

and sensor placement following the SENIAM recommendations [27]. The designated areas on their arms were shaved and cleansed with alcohol. A small amount of conductive gel was applied between the electrodes and the skin to reduce impedance and enhance signal acquisition. Based on the nature of our pHRI task detailed above, two EMG sensors were attached to the participants' arms to acquire data from the lateral deltoid (LD) and posterior deltoid (PD) muscles in our primary pHRI experiments.

In each trial, we measured the human force, the end-effector position of the robot, and surface EMG signals during the experiments. We also recorded the level of subjective rating of fatigue perceived (SRF) by the participant after each cycle and the number of cycles until the onset of fatigue (see Fig. 3.1).

3.3.2 Participants

Training experiments involved 10 participants with an average age of 22.5 ± 1.9 years, an average height of 177 ± 7.4 cm, an average body mass of 76.9 ± 13.6 kg with a fat ratio of $15 \pm 3.6\%$, and an average body mass index (BMI) of 24.3 ± 2.2 kg/m². Each participant performed the task three times under each admittance damping (i.e. a total of 6 trials), with a five-minute rest period between repetitions. Hence, there were a total of 60 trials in the experiment (10 participants $\times$ 2 admittance dampings $\times$ 3 repetitions). The average number of cycles until the onset of fatigue was 23.3 ± 6.9 and 24.2 ± 7.6 under the admittance dampings of $b = 275$ kg/s and 300 kg/s, respectively.

Participants received both verbal and visual instructions on the placement of EMG electrodes and sensors, the robot, and the experimental protocol before the experiments. They completed two familiarization sessions on separate days before the actual experiment, during which they performed the task twice until the onset of fatigue. These training sessions were conducted to ensure that participants were adequately accustomed to the task before the actual trials.

3.4 Subjective Rating of Fatigue

The Borg scale [28] was used to evaluate the rate of perceived exertion by the participants in our pHRI experiments. The Borg CR10 is a scale varying from 0 (no fatigue) to 10 (fatigue) and has been used in earlier studies in the domains of sports biomechanics, kinesiology, and rehabilitation. Participants received both verbal and visual instructions on the fatigue rating scale before the experiments. After each cycle of an experimental trial, they rated their fatigue level, starting from an initial score of “0” and progressing to “10,” a degree at which point they could no longer continue the task.

3.5 Machine Learning

3.5.1 Data Processing

The following features were extracted from the measured EMG signals to be used in the ML models: a) *Frequency-Based Features*: MNF and MDF are frequently utilized in EMG studies. In addition, we used the total power of the signal (TP), which is the sum of the squared power spectral density values over all frequencies, as the feature. b) *Time-Based Features*: The RMS amplitude of the filtered and rectified EMG signal was used as a feature.

Each cycle of an experimental trial was divided into 3 equal intervals, and the minimum and maximum values of the EMG features (MNF, MDF, TP, and RMS) were extracted for each muscle. For the extraction of frequency-based features, the raw EMG signals were filtered with a band-pass Butterworth filter having lower and upper cutoff frequencies of 5 Hz and 500 Hz, respectively [29]. Afterwards, the resulting signals were normalized by using Maximum Voluntary Contraction (MVC) muscle activation values. This enabled us to compare EMG activity in the same muscle on different days or in different individuals or between muscles. For extracting time-domain features, we then applied full-wave rectification by taking the absolute value of the normalized EMG signals.

3.5.2 Modeling

We developed subject-specific ML models rather than a single model across all participants because inter-subject variability in EMG features and fatigue progression patterns is high, and personalized models captured each subject's unique neuromuscular response to repeated exertion.

We trained and tested three regression models: Random Forest, XGBoost, and Linear Regression. Random Forest and XGBoost are based on decision trees and can capture non-linear relationships in regression. On the other hand, A linear regression model was utilized for the baseline comparison with Random Forest and XGBoost.

The EMG features (MNF, MDF, TP, and RMS) extracted for each cycle were fed to our subject-specific ML models as input. Features were extracted on a per-cycle basis, where each motion cycle—segmented according to position—was treated as a single data sample for the ML model. For each subject, 6 trials were performed with an average of 23 cycles per trial, yielding approximately 138 samples per subject. Each sample comprised a total of 16 features, derived from eight features (minimum and maximum values of MNF, MDF, TP, and RMS amplitude) computed for each of the two EMG channels across the cycle. The output was the fraction of cycles to fatigue (FCF).

A hyperparameter search was performed to identify the optimal configuration for each ML model. The Random Forest model was configured with 200 decision trees and a maximum depth of 8. The XGBoost model was configured with 200 boosting rounds and a maximum tree depth of 5, a learning rate of 0.05, and regularization parameters $\alpha = 0.5$ (L1) and $\lambda = 2.0$ (L2).

3.6 Deep Learning

We employed a CNN model for deep learning. Raw EMG signals were filtered first, subsequently normalized by the muscle activation values of MVC as described in the ML section, and then transformed into the frequency domain via Short-Time Fourier Transform (STFT) with 400-sample windows and 300-sample overlap, restricted to

the 10–250 Hz frequency band. The resulting spectrograms were log-transformed and subsequently z-score normalized before being input to the model. The output was the fraction of cycles to fatigue (FCF).

A hyperparameter search was performed to identify the optimal configuration for the CNN model. The CNN model consisted of three convolutional blocks (32, 64, and 128 filters) with batch normalization and dropout (0.3), followed by fully connected layers of 128 and 64 units. Training employed the Adam optimizer (learning rate = 0.001), batch size = 16, and early stopping with a patience of 40 epochs. Data were partitioned into 80% training and 20% validation sets.

3.7 Cross-Task Generalization

To provide a proof-of-concept evaluation of the cross-task generalization capability of the proposed fatigue estimation models, additional experiments were conducted with a single participant: (i) a vertical movement task involving repetitive up-down movements along the Z-axis for a total distance of 40 cm, and (ii) a planar circular movement with a diameter of 20 cm on the XY plane (see the axes in Fig. 3.1). For the vertical movement task, to test the robustness of the proposed approach not only to the movement direction but also the recruitment of different muscles, EMG signals were recorded from the anterior deltoid (AD) and lateral deltoid (LD) muscles, while the circular movement task utilized EMG signals from the same muscle pair (PD and LD) used in the primary dataset. The participant performed 6 trials again for each task. The data collected for additional tasks were not included in the training phase of the learning models and served as cross-task evaluations to assess the model’s robustness to changes in movement direction, arm kinematics, and muscle recruitment.

Chapter 4

RESULTS

4.1 EMG Features

Fig. 4.1 illustrates the percent change in EMG features relative to the initial cycle, plotted against the FCF. Given the variability in muscle activation levels among subjects and the differing number of cycles each subject completes before reaching fatigue, normalizing both the EMG data to the initial cycle and the number of cycles to the maximum cycles is essential. This approach enables the aggregation and comparison of data across participants within a unified framework. As shown in Fig. 4.1, MNF and MDF decrease with the number of cycles, while TP and RMS increase. The linear regression models were fitted to illustrate the overall trends between changes in EMG features and the fraction of cycles to fatigue (FCF). The considerable variation in R^2 values across participants reflects inter-individual differences in EMG activation patterns, thereby supporting the need for subject-specific learning models.

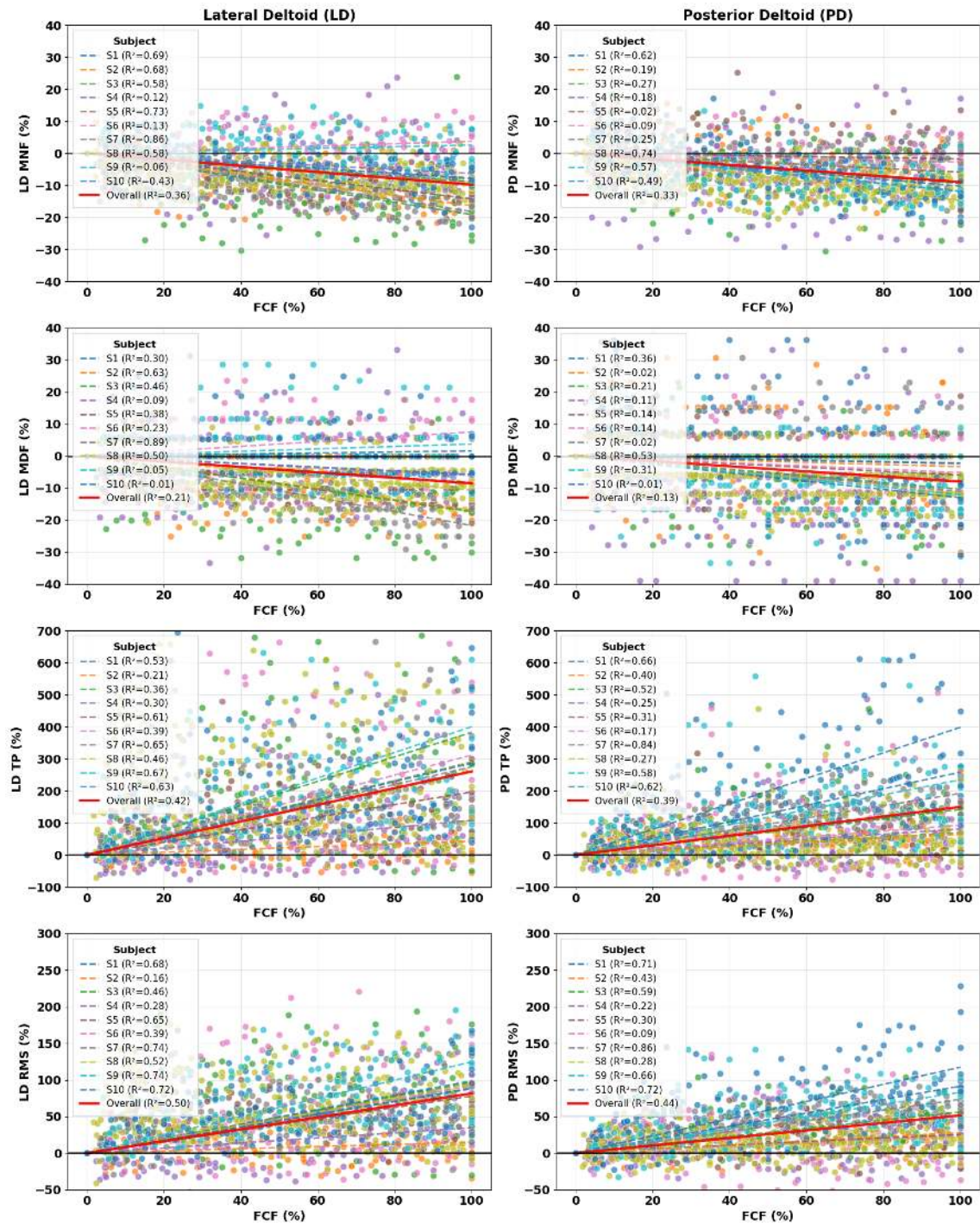


Figure 4.1: Relative change in the maximum values of MNF, MDF, TP, and RMS amplitude with respect to the initial cycle plotted against the fraction of cycle to fatigue (FCF). Each row represents one feature, while the left and right columns are for the data collected from the LD and PD muscles. In each plot, a dot represents a feature for a cycle, and the data of each participant is represented by a unique color. The dashed lines in each plot represent the individual linear fits for each participant, while the solid line depicts the linear fit for the average across all participants to illustrate the general trend.

4.2 Subjective Rating of Participants

Fig. 4.2 illustrates the subjective rating of fatigue (SRF) plotted against FCF. Although the original subjective scores were collected on a 0–10 scale in accordance with the Borg CR10 scale, the values were linearly interpolated and normalized to a percentage scale (0–100%) to ensure compatibility with the fraction of cycles to fatigue (FCF) metric. As shown from the plot, there is a high correlation between FCF and SRF ($R^2 = 0.98$), suggesting that the FCF value estimated by the learning models is a good indicator of fatigue perceived by the participant.

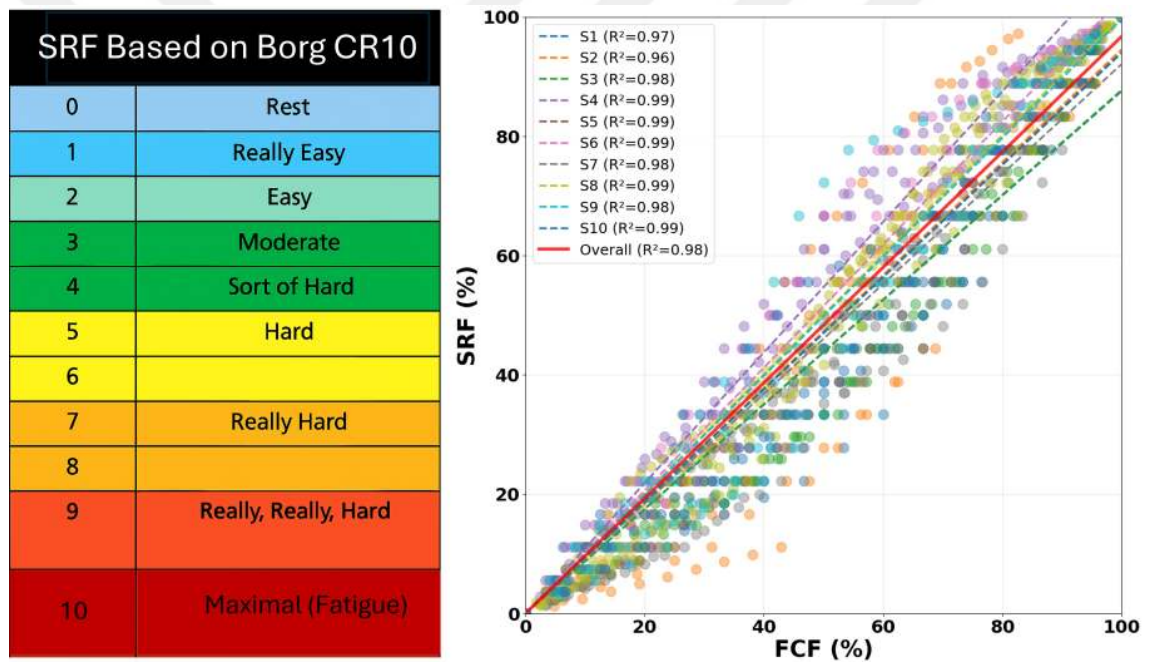


Figure 4.2: a. Subjective level of fatigue perceived by the participants (SRF) was evaluated using Borg CR10 score. b. The fraction of cycles to fatigue (FCF) versus SRF. Each dot in the plot represents an SRF value of a participant recorded for a cycle. Data for each participant is represented by a unique color in the plot. The dashed lines represent the individual linear fits for each participant, while the solid line depicts the linear fit for the average across all participants to illustrate the general trend.

4.3 Learning Models

Root Mean Squared Error (RMSE) was employed as the primary metric to evaluate the performance of the ML and DL regression models in this study. Fig. 4.3 shows

the mean RMSE values computed for each participant, averaged across all trials, for the respective regression models. Since the learning models output the estimated fatigue in percentage (FCF), RMSE values are also reported in percentage. Model performance was assessed using a trial-wise 6-fold cross-validation scheme, implemented as a Leave-One-Trial-Out (LOTO) procedure. Specifically, for each fold, the data from one of the six trials performed by a participant was held out for testing, while the remaining five trials were used for training. This procedure was repeated across all six possible trial selections. After each iteration, RMSE was calculated on the held-out trial, and the final performance was reported as the average RMSE across the six folds.

As shown in Fig. 4.3, the CNN model yielded the lowest RMSE values across participants, while the Linear Regression largest. When averaged over all participants, the RMSE was $20.8 \pm 4.3\%$, $23.3 \pm 3.8\%$, $24.8 \pm 4.5\%$, and $26.9 \pm 6.1\%$ for the CNN, Random Forest, XGBoost, and Linear Regression models, respectively. Feature importance analysis using the Random Forest model indicated that MNF contributed the highest predictive relevance for estimating FCF (43%), followed by RMS amplitude (22%), TP (22%), and MDF (14%). A similar result was obtained by the feature importance analysis using the XGBoost model.

4.4 Cross-Task Generalization

Cross-task generalization experiments were conducted with a single participant (S1 in Fig. 4.3). Subject-specific learning models were trained on EMG data from the lateral movement task, initially using 6 trials and subsequently an extended dataset of 18 trials (6 original + 12 additional) to assess the effect of training set size on model performance. These models were then applied without retraining or fine-tuning to new EMG datasets obtained from two unseen tasks: (i) vertical repetitive movements along the Z-axis and (ii) circular movements on the XY-plane. Model generalization performance was quantified using the same regression metric (RMSE) employed in the primary experiments. The RMSE values for the vertical movement task trained on 6 trials (Fig. 4.4a) were $27.1 \pm 2.5\%$ for CNN, $20.3 \pm 2.5\%$ for

Random Forest, and $20.4 \pm 2.4\%$ for XGBoost. When the training set was extended to 18 trials (Fig. 4.4b), the corresponding RMSE values changed to $15.8 \pm 3.4\%$, $20.6 \pm 2.7\%$, and $22.1 \pm 3.5\%$, respectively. For the circular movement task, the RMSE values obtained with 6 training trials (Fig. 4.4c) were $30.1 \pm 2.3\%$ for CNN, $25.6 \pm 4.9\%$ for Random Forest, $28.3 \pm 5.7\%$ for XGBoost, and $47.8 \pm 20.8\%$ for Linear Regression. With the training set expanded to 18 trials (Fig. 4.4d), the RMSE values changed to $22.4 \pm 3.2\%$, $23.4 \pm 5.0\%$, $25.1 \pm 5.6\%$, and $27.2 \pm 7.7\%$, respectively. Note that the Linear regression model trained with the data of either 6 or 18 trials of the lateral movement failed to regress (i.e. generated an average RMSE value larger than 100%) when tested on the data of the vertical movement task. It also generated high RMSE values when tested on the circular movement task.

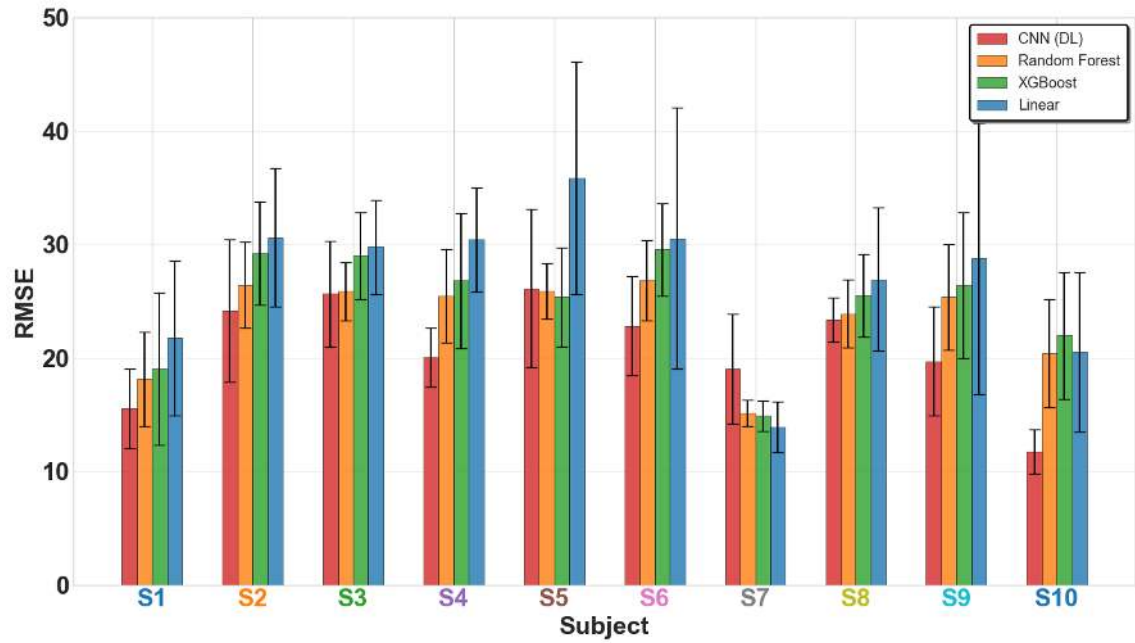


Figure 4.3: Bar plots illustrating the mean RMSE values of each participant for the primary task, averaged across all trials, for the different regression models.

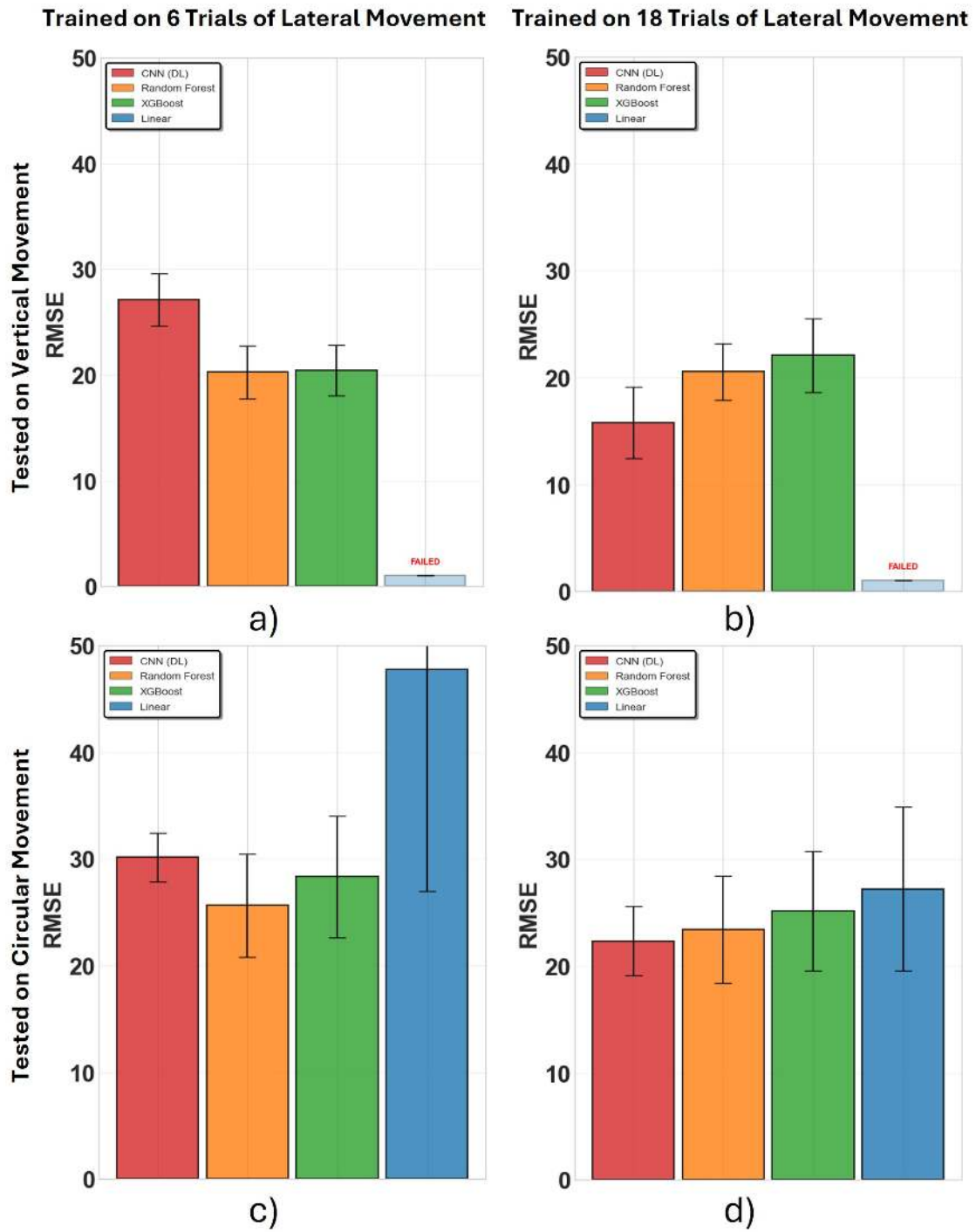


Figure 4.4: Mean RMSE values for participant S1 in cross-task experiments. Panels (a,c) correspond to models trained on 6 lateral trials and tested on vertical and circular tasks, while panels (b,d) correspond to models trained on 18 lateral trials and tested on the same tasks.

Chapter 5

DISCUSSION

This investigative study introduces a learning-based approach to estimate the progression of human effort towards muscular fatigue in dynamic and repetitive physical human-robot interaction (pHRI) tasks, based on surface electromyography (sEMG) signals. Earlier data-driven ML/DL methods for fatigue estimation largely relied on classification-based formulations. In contrast, our regression-based approach models the continuous progression of fatigue, allowing for closer monitoring of physiological changes and supporting timely intervention and adaptive control in dynamic tasks.

The results of our study show that both frequency-domain (MNF, MDF, TP) and time-domain (RMS amplitude) features of EMG signals evolve systematically with the progression of task (Fig. 4.1). The trends observed in EMG feature progression (decreasing MNF and MDF and increasing RMS and TP) reflect underlying physiological mechanisms such as decreased muscle fiber conduction velocity and increased motor unit recruitment as suggested in [30]. On the other hand, no significant changes in human-applied force were observed across cycles during task progression (see the second row of time-plots in Fig. 3.1), indicating that participants consistently generated sufficient force to track the desired trajectory despite changes in their muscle activity. Among the EMG features, MNF appeared to have the highest predictive power for estimating the fraction of cycles to fatigue (FCF). The strong correlation observed in our study (Fig. 4.2) between subjective fatigue rating (SRF) and FCF validates the use of FCF as a reliable metric for estimating fatigue in cyclic pHRI tasks.

Our study demonstrates that constructing a cross-subject ML/DL model for fatigue estimation is challenging due to substantial inter-subject variability arising from physical and physiological differences. This variability was evident in the spread

of R^2 values obtained when fitting EMG features to the fatigue cycle fraction (FCF) (Fig. 4.1). Notably, participants exhibited different activation strategies for the LD and PD muscles, with some relying more heavily on LD while others engaged PD to a greater extent. Consequently, we adopted subject-specific learning models for fatigue estimation. Even at the subject level, the root mean square error (RMSE) of FCF estimation ranged from 12% to 26%, averaging 21% across participants for the best model (CNN). This error magnitude is attributable primarily to the dynamic nature of the task, which complicates acquisition of high-quality EMG signals compared to isometric contractions under static loading. Additional intra-subject variability in EMG features was observed across trials, although this was less pronounced than inter-subject variability. Performance across different ML models was comparable: Random Forest and XGBoost both achieved an RMSE of approximately 24%, while even the Linear Regression model yielded similar accuracy of 27%, though the standard deviation from the mean was the largest.

Prior studies have predominantly focused on static tasks involving isometric contractions or used computationally intensive musculoskeletal simulations, limiting real-time applicability. This work advances the state-of-the-art by proposing a data-driven solution for dynamic tasks using lightweight learning models that can be deployed for real-time fatigue estimation. Unlike previous efforts, which required musculoskeletal models or ODEs for modeling the force-fatigue relation, our method offers a simpler implementation. By inputting the percent relative change in EMG features with respect to the first cycle rather than their absolute counterparts into the ML models, we account for intra-subject variability in baseline muscle activation and endurance capacity, thereby enhancing the estimation capacity of the subject-specific learning models, especially in cross-tasks.

In cross-task validation experiments (Fig. 4.4), we demonstrated that the ML models (Random Forest and XGBoost) trained with the relative changes in EMG features are robust to changes in motion kinematics (lateral vs vertical and circular movements) and muscle recruitment (data was collected from LD and PD muscles in lateral and circular movement tasks, while LD and AD for the vertical movement task). When the ML models were trained on either 6 or 18 trials of the lateral

movement data, their test performances on the vertical and circular tasks showed little degradation, likely because both training and testing phases used EMG features normalized relative to the first cycle. In contrast, the CNN model yielded a higher average RMSE than the ML models when trained on 6 trials (Figs. 4.4a and 4.4c), possibly due to differences in the frequency content of the training and testing EMG signals. However, its performance improved when trained on 18 trials of the lateral movement (Figs. 4.4b and 4.4d), as the larger dataset provided more representative EMG patterns and enhanced generalization across tasks.



Chapter 6

CONCLUSION

This work developed a regression-based machine learning framework for estimating muscle fatigue in dynamic physical human-robot interaction tasks using surface EMG signals. The approach provides continuous fatigue monitoring rather than discrete classification, which is useful for real-time applications in collaborative robotics. The experimental results showed that EMG features change systematically with fatigue progression during cyclic tasks. Mean frequency and median frequency decreased over successive cycles, while RMS amplitude and total power increased, consistent with known physiological mechanisms of muscle fatigue. Mean frequency provided the best predictive performance for estimating the fraction of cycles to fatigue.

Significant inter-subject variability was observed in muscle activation patterns and fatigue progression, requiring subject-specific models rather than generalized approaches. The subject-specific models achieved root mean square errors of 20.8% for CNN, 23.3% for Random Forest, 23.8% for XGBoost, and 26.9% for Linear Regression. These error levels reflect the challenges of acquiring clean EMG signals during dynamic movements compared to static conditions. Using relative EMG feature changes with respect to the first cycle improved model robustness compared to absolute feature values. This normalization approach accounted for individual differences in baseline muscle activation and enhanced cross-task generalization. Models trained on lateral movement data performed well on vertical and circular movement tasks with minimal accuracy loss.

The correlation between objective fatigue estimates and subjective fatigue ratings validated the fraction of cycles to fatigue as a practical metric for quantifying muscle fatigue in cyclic tasks. This confirms the clinical relevance of the approach. The data-driven framework offers computational advantages over musculoskeletal

simulations and extends beyond the static contractions studied in previous works. The lightweight implementation makes it suitable for real-time deployment in collaborative robotic systems where fatigue monitoring can inform adaptive control strategies. This work provides a practical foundation for human-aware robotics applications. The framework can support performance optimization and safety considerations in physical human-robot collaboration scenarios. Future work should validate the approach with larger populations and integrate it with adaptive robot control systems.

Some limitations of the proposed approach should be acknowledged here. First, the dataset was collected from a specific group of participants who were university students, which may limit generalizability across populations with different physical and physiological characteristics. Second, the model assumes homogeneous fatigue progression across different muscles, although muscle volume, type, and activation patterns may differ.

Future research should explore integrating EMG signals with joint kinematics and external force measurements to develop hybrid models that leverage the physical interpretability of musculoskeletal simulations (e.g., using OpenSim) with the predictive power of data-driven methods. Including diverse tasks, body segments, and real-world scenarios (e.g., manufacturing, rehabilitation) would improve robustness. Additionally, closed-loop robotic controllers that adapt based on real-time fatigue estimates can be developed and validated in longitudinal studies.

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