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PLEASE CITE THE PUBLISHED VERSION

https://doi.org/10.1109/THMS.2023.3259139

PUBLISHER

Institute of Electrical and Electronics Engineers

VERSION

AM (Accepted Manuscript)

An Incremental Learning Approach to Detect Muscular Fatigue in Human-Robot Collaboration

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Abstract— **Human-Robot Collaboration aims to join distinctive strengths of humans and robots to compensate weaknesses associated with each party, and thus, to enable synergetic effects. Robots are characteristically considered fatigue proof. Hence, they are utilized to assist human operators during heavy pushing and pulling activities. To detect physical fatigue or high payloads held by a human operator, wearable sensors such as Electromyographys (EMGs) are deployed. The EMG data is typically processed via Machine Learning, which includes training models offline before an application in an online system. However, these approaches often demonstrate varying performances between offline and online applications, due to subject specific characteristics within the data. An opportunity to tackle this challenge can be found in Incremental Learning, as these models purely learn online and constantly fine-tune the model's structure. In this paper, a Mondrian Forest is applied to predict payloads and physical fatigue of human operators during an assistance scenario with a collaborative robot. An experiment was conducted with a total of 12 participants, where payload was increased until participants initiated an assistance request from a UR10 cobot. This allowed for testing whether the Mondrian Forest can accurately predict the payload and fatigue levels from the acquired EMG signals. Overall, the approach demonstrates a promising potential towards higher awareness when an operator might require assistance from a robot, and ultimately towards a more effective Human-Robot Collaboration.**

***Index Terms*—EMG, Human-Robot Collaboration, Incremental Learning, Mondrian Forest, Muscle Fatigue**

I. Introduction

HUMAN-Robot Collaboration is considered as a key paradigm to combine the best of both worlds: a robot's endurance, speed and precision, with human dexterity, perception and adaptability [1]. At the same time, this is also envisioned to compensate weaknesses associated with each party [2]. Human weaknesses typically include being susceptible to fatigue and stress, which can apply both mentally and physically [3], [4]. Consequently, Human-Robot Collaboration aims to assign physically demanding tasks to the robot, or to assist the human when lifting heavy payloads [5]. In such physical collaborations, robots support human operators via force amplification to perform heavy pushing or pulling activities [6], [7]. Thus, it does not only allow for creating a more ergonomic environment, but also to mitigate potential physical disadvantages caused by age, sex, or disability.

One of the challenges, however, is to establish a collaborative robot's awareness of its human partner's need for assistance [4]. For this purpose, wearable devices have faced an increased popularity to enable sensing of the human operator's state [8], [9]. In the case of physical interactions, electromyography's (EMG) are deployed, which allow for measuring human muscle activity [10], [11]. Since interpretation and integration of these signals is often challenging, Machine Learning is utilized to classify patterns within the data. Approaches are typically based on supervised training offline, before an application of a trained model in an online system. These models often demonstrate considerably lower classification performances in an online system, than during the training sessions prior [12]. This effect can be observed during different recording sessions even for the same individual [13]. The issue of varying performances and high manual training and programming efforts could be tackled through advances in Machine Learning regarding Incremental Learning. Incremental Learning algorithms purely learn online, which enables constant automatic fine-tuning and adaption of the models [14], [15]. Therefore, they could allow to minimize the training and programming effort, while delivering more persistent results.

In this work, an Incremental Learning approach based on a Mondrian Forest is utilized to predict payload and muscle fatigue from EMG data during a Human-Robot Collaborative task. Overall, the approach offers a promising potential, of Machine Learning models learning "on the fly", and to adapt to the uniqueness of human operators in terms of strength and endurance.

Manuscript received XXXX XX, XXXX; revised XXXX XX, XXX; accepted XXXX X, XXXX. Date of publication XXXX XX, XXXX;
(Corresponding author: Achim Buerkle.).

This work was funded by the EPSRC as part of the Digital Toolkit for optimization of operators and technology in manufacturing partnerships project (DigiTOP; EP/R032718/1).

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II. RELATED WORK

Human-Robot Collaboration is widely considered as the highest form of Human-Robot interactions, since it includes joint tasks, shared workspaces, a common aim, and permitted physical contact between the two parties [16]. To establish an effective communication for physical interactions, two options are plausible: direct control [17], or deploying wearable sensors such as EMGs. EMGs are utilized to detect muscle contraction forces of the human operator [13]. This is due to contraction of muscles generating electrical activity, which can be measured on the surface [18]. An increase in mean amplitude and a decrease in frequency are indicators of intense muscle contraction [19]. The EMG signals are typically acquired from upper-limbs, since they are mainly involved in the physical interactions with a robot [10]. Subsequently, the EMG data can provide insights on human intentions, such as applying forces in a certain direction [20]. It can also be utilized to detect human muscle fatigue due to high payloads or endurance stress [19], [21]. In both cases, a collaborative robot could assist its human partner to create more ergonomic working conditions [10], [13]. This could prevent strain injuries, as well as long-term health issues related to muscular fatigue. Long-term damages are often referred to as musculoskeletal disorders in this context, which might not appear immediately [19]. Thus, overall, there is a strong motivation to detect and integrate these signals into the Human-Robot Collaborative loop.

Measurement and integration of EMG signals into a Human-Robot Collaborative system, however, is often challenging. This is due to subject specific characteristics within the EMG data. EMG data streams demonstrate unique features for each individual [13], [22]. A change in these features can be observed even during different recording sessions for the same person [13]. Consequently, manual fine-tuning and programming efforts are often required to adapt to these features. Hence, Machine Learning is utilized to identify relevant patterns and to perform continuous classification. For this purpose, different strategies can be applied.

The most commonly used processing and interpretation technique is based on Fourier Transform in conjunction with a Machine Learning classifier, referred to as "Standard" in Fig. 1. A wave transform, such as Fourier Transform is required since most human physiological data follows sinusoidal patterns [18]. Moreover, raw EMG signals often contain high levels of noise. Thus, filters are applied such as Butterworth filters with a cut off frequency of 2Hz-20Hz [13]. Afterwards, relevant features (frequency, amplitude) can be extracted to train a Machine Learning classifier. This feature extraction is described to have a larger impact on the classification performance than the selection of the classifier itself [12], [13]. The classifiers are trained offline until they reach a satisfactory performance before they are applied online. According to [12], Support Vector Machines and Linear Discriminant Analyses are commonly used to classify EMG signals. One of the advantages of this methodology is its high transparency. The results of each intermediate step, such as the feature extraction, can be visualized. The disadvantages, however, are twofold: Firstly, many systems obtain high classification accuracies during offline training. Yet, the online performances of such systems are often significantly lower. Secondly, programming and

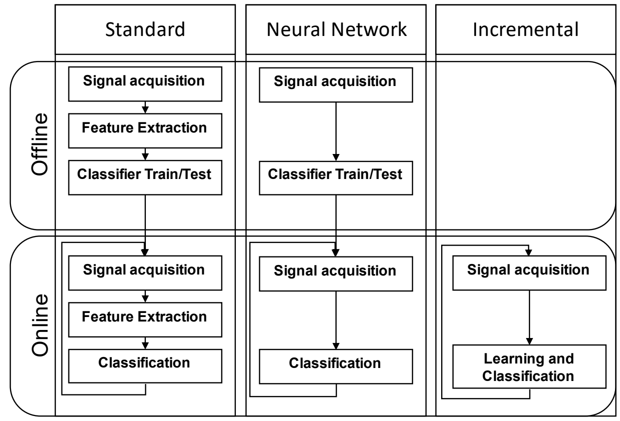

Fig. 1 Data processing and machine learning methodologies to process EMG signals (adapted) [25]

training the models requires high manual efforts [12], [13]. Thus, other approaches have been established to minimize manual fine-tuning.

In recent years, Artificial Neural Networks (ANNs) including various variations have gained a high research interest. In the case of human sensor data, the main idea is to stream raw data into the classifier. Due to their advanced nature, the ANNs are expected to identify relevant patterns by themselves [20], [23]. In these approaches, time-series based ANNs such as Recurrent Neural Networks (RNNs) and Long-Short Term Memory RNNs (LSTM-RNNs) delivered promising results. The advantages of this methodology were the lower variance in prediction accuracy between offline and online systems. Moreover, manual fine-tuning efforts are substantially lower than during the "Standard" methodology. Disadvantages, however, are the large quantities of training data required to train a model. This can also result in several hours of training time until a classifier can be used online.

An opportunity to cope with the challenges of excessive training times and varying accuracies between offline and online systems can be found in Incremental Learning. Incremental Learning algorithms offer the ability of purely learning online or "on the fly" [15]. They typically offer the following characteristics [14], [15]:

- Ability of life-long learning
- Ability to incrementally fine-tune the model's performance
- No prior knowledge about the data or its properties are required

Thus, this would allow for using an Incremental Learner to continuously adapt to a human operator, while improving its performance over time. There are, however, two challenges. Namely: the plasticity-stability dilemma, which entails the model must continuously learn new knowledge, without forgetting previously obtained knowledge [15]. And secondly, convergence time, which includes the time to perform a learning operation and classification [24]. Generally, the more complex a dataset and the subsequent model, the longer the convergence time. These factors require investigation during an application to predict muscular payloads and fatigue from EMG data in Human-Robot Collaboration.

III. Approach

In order to establish an effective Human-Robot Collaboration, where both parties can compensate each other's weaknesses, a high mutual awareness is required. While there are co-manipulation and load sharing approaches in place, these do not necessarily qualify as Human-Robot Collaboration, since the robot is lacking the cognitive skills to determine when an operator requires assistance. Hence, in this paper, wearable sensors are deployed to detect muscle activity, where the acquired signals are interpreted via Incremental Learning, which allows for learning and classifying "on the fly". Thus, this is envisioned to predict when an operator reaches high levels of payload leading to muscular fatigue, and consequently, requires assistance from the collaborative robot.

In a first step (Fig. 2), wearable EMGs are deployed on an operator's upper limb muscles, which are primarily involved in lifting or holding activities (bicep and forearm). EMGs are chosen as they are the most popular sensor for detecting muscle activity [13]. However, simply feeding the acquired signals into the Incremental Learner does not yield sufficient results. This is mainly due to the nature of the EMG signal, which follows sinusoidal wave patterns and also contains noise (such as powerline interference at 50-60Hz in Europe). Therefore, a feature extraction step is added, which entails a low bandpass filter to remove noise, followed by a short-time Fourier transform. The resulting spectrum analysis (frequency, amplitude, and phase of the spectrum) is then used in the Incremental Learner. Main advantages of the Incremental Learner in this context are twofold: First, it allows for continuous adaptation to the uniqueness of a person (individual muscle activity signals, training/fitness level). Second, it allows for distinguishing different levels of payload from EMG signals over time. For instance, if a non-incremental classifier such as a Support Vector Machine or a Random Forest is trained offline with three different payloads (low, medium, high), it can only distinguish these three classes in an online application. In contrast, an Incremental Learner can learn and distinguish new classes during an online application. In the example this could include: "very low", "low", "medium", "high", and "very high" payloads. Consequently, Incremental learners offer the opportunity of lowered fine-tuning and programming efforts alongside, potentially higher prediction accuracies in an online application.

In the following, this methodology, also shown in Fig. 2, will be applied, and further explained in the subsections: (A) data acquisition, (B) low bandpass filter, (C) short-term Fourier Transform, and (D) learning and classification.

A. *Data Acquisition*

Based on the application, EMG sensors can be placed on various muscles, which are required to perform an activity. For example, the human upper limbs, which are predominantly involved in performing tasks and collaboration with robots, consist of a wide variety of muscles. Thus, EMG signals could be obtained regarding movements and forces in the shoulder, arms, and fingers [13]. In the current context, signals will be acquired from the biceps brachii and brachioradialis (forearm), since these muscles are mainly involved during lifting or steady holding of a workpiece. Overall, correct placement and a careful selection of EMG device (channels, sampling rate) are essential since both factors have a significant impact on the signal quality. Even advanced classifiers such as ANNs achieve low prediction accuracies if the EMG signal quality is poor [25].

B. *Low Bandpass Filter*

Although the general idea of Incremental Learning is to minimize manual programming and filtering efforts, this might not be fully applicable in the current context. As described in Section II, EMG signals are susceptible to contain noise, which could interfere with prediction accuracies. Noise sources

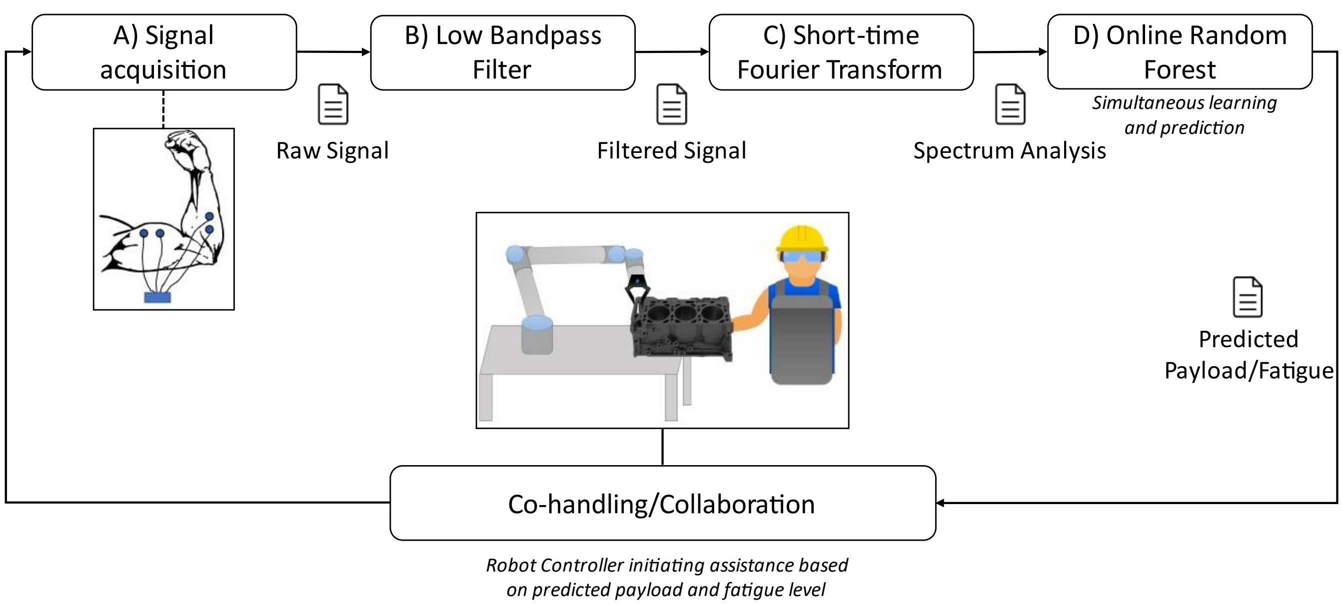

Fig. 2 Overview of the approach: Signal acquisition via EMG sensors on different muscles, filtering noise such as powerline interference at 50-60Hz, performing a short-time Fourier Transform to retrieve underlying frequencies and intensities, performing the online/incremental learning via the Mondrian Forest. The predicted payload and fatigue levels are then communicated to the collaborative robot, which in turn can assist the operator.

include ambient noise, such as electromagnetic radiation from power sources, as well as the inherent noise in electronic equipment itself [13]. Therefore, an additional pre-processing step was added which includes a low-pass filter with a cut-off frequency at 30Hz. This is aligned with literature, where most approaches consider the frequency band of 2-30Hz to retrieve relevant muscle activity features, while removing the majority of dominant external noise sources [13]. The filtered signal is used in a short-time Fourier Transform.

C. *Short-time Fourier Transform*

Similar to a guitar where a cord consists of different notes, EMG sensors provide muscle activity data in a complex signal within a time domain. The signal consists of different frequencies and associated intensities. Consequently, it is necessary to perform a wave transform to retrieve relevant features (underlying frequencies and their intensity), which can be mapped to payloads and muscular fatigue. In this approach, a short-time Fourier Transform (STFT) is chosen, as it allows for a fast processing of the signal [26]. The STFT is performed on 0.75s interval windows and an overlap of 0.05s. The overlap of windows prevents loss of features if they occur at the beginning or the end of a window. The resulting spectrum analysis is then used in the Incremental Learner. Rather than selecting relevant features (frequencies) manually, all resulting features of the STFT are used. Thus, the Machine Learning algorithm is able to identify correlating frequencies with payloads and muscular fatigue by itself.

D. *Learning and Classification*

Incremental and online learning offer a wide variety of classifiers [14]. One of the most prominent is an Online Random Forest (ORF), due to its high accuracy, scalability and robustness [24]. In this work, a sub-category of ORFs is chosen in Mondrian Forest, which is described to obtain comparable accuracies with its state-of-the art batch/offline counterparts on the same datasets [24]. Mondrian Forests consist of several decision trees which are generated on random subsamples of the data. The structure of the decision tree, shown in Fig. 3, part A, is generated automatically. Each tree consists of split nodes, which contain the decision logic. For instance, if the signal intensity of a certain frequency is above or below a threshold. The labels or classes are at the end of a “branch” and referred to as leaf nodes. In the current context, these leaf nodes contain payload and associated fatigue levels of operators from “very low” to “very high”. Both: the split nodes and the leaf nodes would be unique for each operator depending on the signals and the variety of payload handled. The more complex the classification logic, due to a combination of split nodes, the higher the tree complexity would be. Moreover, the model complexity also depends on the number of trees in a model. The number trees, however, can be manually selected as a hyper parameter. Typically, the performance increases with a higher number of trees until a saturation is reached. The individual predictions of the trees are merged based on voting or averaging, as shown in Fig. 3, part B. Afterwards, a final prediction will be made.

To enable Incremental Learning, the model learns and updates itself purely online (on-the-fly). Thus, three types of learning operations can be performed: introduce a new split node (Fig 2, part C), update the split condition in an existing node (Fig 2, part D), and finally add a new class via splitting a leaf node into two (Fig 2, part E). In the current context, introducing a new split node can be based on a new feature (frequency and frequency intensity of one EMG sensor and the associated muscle). A split condition can be updated in an existing node, for example, a different threshold for frequency

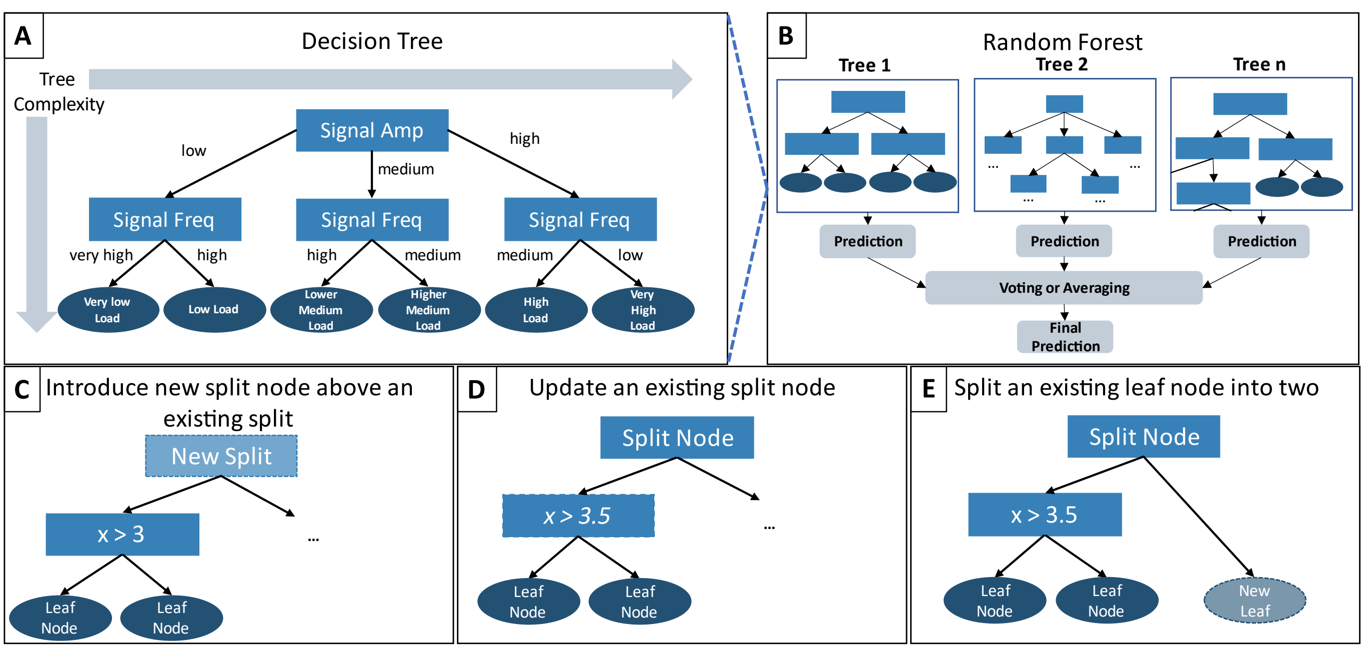

Fig. 3 Mondrian Forest structure: each forest consists of decision trees. Part A shows a decision tree and its key elements: split nodes (blue) containing the decision logic; leaf nodes (dark blue) which are the classes/labels that the model is predicting. The higher the depth (horizontally and vertically) of the tree, the higher the complexity. Part B shows the forest structure, in which several decision trees make a prediction that is then aggregated to a final prediction of the model. Part C, D, and E show the incremental learning operations which are continually performed “on-the-fly”/online. Note that the tree structure is not a representative example, its simplified structure is intended to demonstrate the learning and classification principle.

intensity is set. Lastly, a new leaf node can be established when new type of payload or fatigue level is identified. For example, from "medium payload" to "low medium" and "higher medium" payloads. These learning and prediction operations are continuously performed, which enables constant fine-tuning of the model.

There are, however, two challenges when applying Mondrian Forests which are namely: Maximizing the prediction performance of the model and minimizing the processing/convergence time. The convergence time depends on the time the model takes to make a prediction and perform a learning operation. Both: the prediction performance and the convergence time can be controlled via the hyper-parameter: *number of trees in the model*. A higher number of trees typically produces a higher prediction performance until a saturation is reached. After this threshold any additional tree in the model does not contribute to an increased performance anymore. At the same time, each additional tree in the model adds to the complexity, and thus, increases convergence time. This is mainly because each tree needs to be updated and maintained during the learning operation.

Thus, on one hand, the convergence time should be kept as low as possible. On the other hand, the prediction performance should be maximized. To obtain this optimum (number of trees), and to validate whether a Mondrian Forest can accurately predict different payloads and muscle fatigue from EMG data, an experiment was performed, which is introduced in the following.

IV. Experiment

The experimental design aims to generate EMG data samples during participants lifting and holding different payloads from low to subjectively high. Where weights are increased until participants manually trigger an assistance request, as soon as they feel fatigued. The EMG data stream is collected and labelled, based on the payload. Thus, this allows for applying the Mondrian Forest, to validate whether it can correctly predict the varying levels of payload and subsequent muscular fatigue from EMG data. Moreover, rather than participants pressing the assistance request manually, the Mondrian Forest is envisioned to identify the fatigue-threshold and to trigger a robotic assistance request automatically afterwards.

The experiment was conducted with 12 participants between 20 and 39 years of age. The participants had various levels of prerequisites regarding exercise and strength. While some participants perform strength/conditioning related exercises 3 times per week and more, other participants stated they did not perform any type of exercise at all. Thus, varying levels of performance are expected during the experiment. Consequently, it can be validated whether the Mondrian Forest can adapt to the uniqueness of participants in terms of EMG signal (variety in strength and muscle size/cross section), as well as the different number of classes to predict (varying levels of payload per participant).

In a first step, EMG data needs to be acquired. For this purpose, 4 Myoware muscle activity sensors were placed on participant's biceps and forearms, as shown in Fig. 4, part A. These sensors provide two output modes as in raw data and already filtered data streams. For the following data processing the filtered data streams will be utilized, which includes the low bandpass filter (Section III part B). Each Myoware device is connected to a Raspberry Pi 3 within the Blue Box, shown in Fig. 4, part B. The blue box contains analogue-to-digital converters, a battery pack, and a WIFI interface. This interface is used for streaming the collected EMG data to the main workstation (ROS master). Further details on the hardware and ROS setup can be found in [9]. Throughout the experiment participants were tasked to stand on the markers and to hold the engine cover, shown in Fig. 4, part A and C. The cover itself has a weight of 8kg, which is not considered particularly heavy.

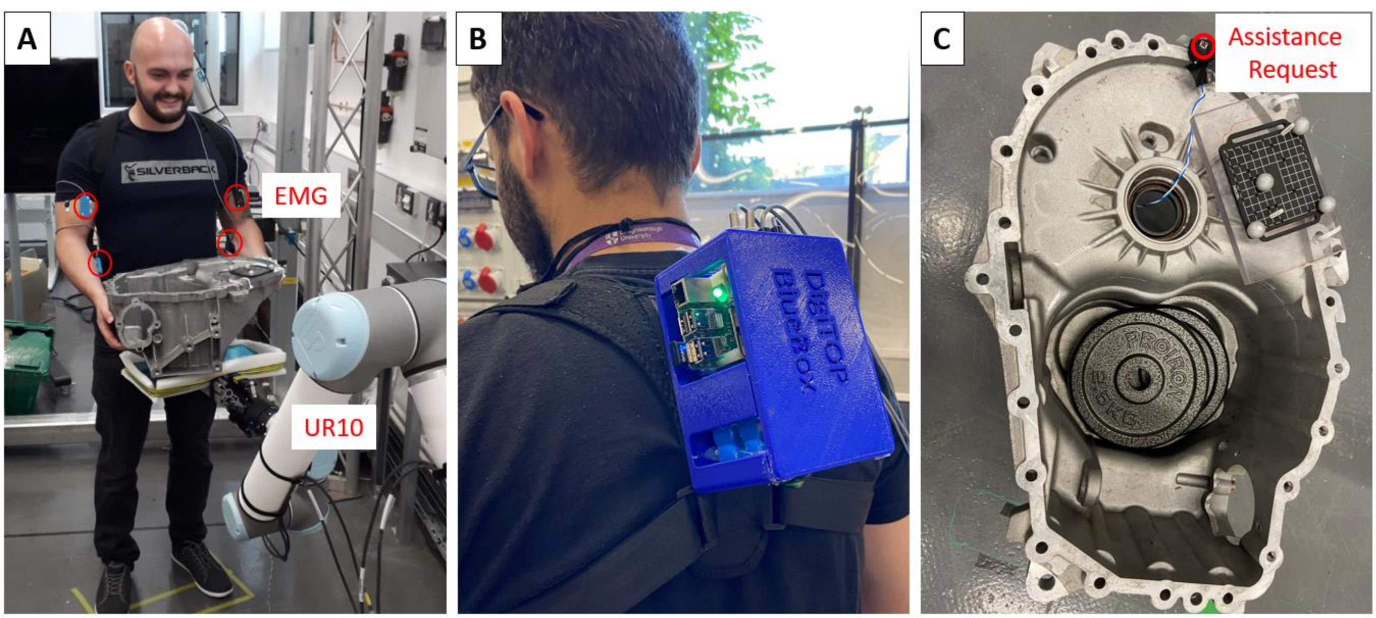

Fig. 4 Experimental setup: Part A shows participants standing on the markers while holding a workpiece. Myoware EMGs are placed on the biceps brachii and brachioradialis (forearm). A UR10 is assisting the participant to lift the payload. Part B shows the Blue Box, which contains a Raspberry Pi 3 and streams the EMG data via WIFI to the ROS master. Part C shows the engine cover including the assistance request button and 2.5kg plates of added weight.

However, one of the specific features of this container is its uneven weight distribution, as it would be faced in an industrial scenario. Subsequently, different levels of muscle activity are expected for left arm and right arm muscles. In order to enable the classification of different payloads, additional 2.5kg weights were added after 20 second intervals. The initial EMG data stream, while holding the 8KG cover was labelled as “0”, after each additional 2.5kg weight, the data label integer was increased by one, e.g., “0” – 8kg, “1” – 10.5kg, “2” – 13kg and so on. The addition of weights did not only increase the payload, but also change the weight balance of the engine cover. Thus, it became increasingly difficult to hold. Though, the main goal was not to test the physical capabilities of participants. Therefore, participants were briefed to press the assistance request button on the engine cover, shown in Fig. 3, part C, as soon as they reached an uncomfortable level. The assistance request button is connected to the ROS master and would trigger a Universal Robots model 10 (UR10) to run a pre-defined assistance program. In the current setup, the UR10 is equipped with a ROBOTIQ 2F-140 gripper and integrated force/torque sensor. The gripper is holding a thin metal plate, which was fitted with a Styrofoam edging to avoid scratching participants. As soon as the assistance button is pressed, the UR10 would slowly move upwards in a straight line, until it touched the engine cover. Afterwards, it would move an additional 7cm upwards at 10kg payload setting to assist the human operator lifting the weight. During this assistance operation, the force/torque readings of the gripper would allow for quantifying the amount of weight that the UR10 is holding.

One of the main drawbacks of the current setup is the UR10’s limited capability to cope with high payloads. As the name suggests, it has a maximum payload of 10kg. However, most participants are expected to hold higher payloads, before pressing the assistance request button. Therefore, the robot could not fully take the burden off the operator, and rather initiate a load-sharing. Nevertheless, this would still relieve stress from muscles and joints.

Overall, different performances of participants are expected regarding holding time and weight, due to varying levels of strength, body composition, and stress tolerance. Hence, this would allow the Mondrian Forest to adapt to the uniqueness of one individual. The EMG data results, as well as the Mondrian Forest learning and prediction performance, are presented and discussed in the following section.

V. Results and Discussion

In this section the results are presented and discussed in two subsections, namely: experimental results and Mondrian Forest learning/optimization results. Where the experimental results show the participant’s individual performance regarding payload, muscle fatigue and associated EMG signals. As for the Mondrian Forest, the results include the payload/fatigue prediction performance, as well as the optimization of performance and convergence time.

A. Experimental Results

At first, the experiment, described in Section IV, was conducted. Overall, different performances regarding payload and holding time before pressing an assistance request were expected, due to the variety of strength and body composition among participants. This expectation was confirmed, as shown in Table I. Participants 3 and 5 pressed the assistance button after one additional 2.5kg weight was added, which equals 30-40s of holding the container. In contrast, participant 2 managed to hold the engine cover until 6 additional 2.5kg weights were added, totaling 130-140s of holding time. Most participants pressed the assistance request after the third increase in weight at 15.5kg payload and 60-80s total. Overall, this highlights the uniqueness of human operators and the subsequent need to adapt to the individual needs and requirements.

TABLE I
Payloads reached before an Assistance request was initiated

Participant	8kg	10.5kg	13kg	15.5kg	18kg	20.5kg	23kg
1	x	x	x	x			
2	x	x	x	x	x	x	x
3	x	x					
4	x	x	x	x			
5	x	x					
6	x	x	x	x			
7	x	x	x	x	x	x	
8	x	x	x	x			
9	x	x	x	x			
10	x	x	x	x	x	x	
11	x	x	x	x			
12	x	x	x	x	x		

This can be achieved by establishing individual, data-driven models, such as based on EMGs. Therefore, EMG data was collected from both left and right arms throughout the experiment, where variations in EMG signals could be observed among different participants. Moreover, variations could also be observed between left arm and right arm signals, due to the uneven load balancing of the container. One low bandpass filtered sample data stream of participant 6 is shown in Fig. 5. For simplification purposes, only data of the left bicep is illustrated. As it can be observed, the signal is increasing after each additional weight. Finally, after the fourth addition of 2.5kg, the participant pressed the assistance request button. Following the assistance request, the robot is slowly moving upwards (peaks on the UR10 F/T z-axis) before it touches the container. Immediately, the forces on the x,y and z axes increase, whereas the EMG signal decreases. In fact, the EMG signal power decreases to the initial levels, when the participant was holding the engine cover without any additional weights. Thus, evidently, the effect of the robot assistance can be observed, where the burden of the load is shared between the operator and the robot.

Yet, in a collaborative scenario, the system is envisioned to detect an operator needing assistance by itself (from EMG sensor data for instance), rather than an operator manually initiating a request by pressing a button. Thus, providing a collaborative robot with cognitive skills regarding its human partner to improve teamwork by compensating each other’s weaknesses. Since the collected EMG signal shows an obvious change in pattern regarding different payloads, high classification performances are expected via Machine Learning. In the following the Mondrian Forest will be applied and optimized to predict the different payloads and the fatigue threshold from the collected EMG data.

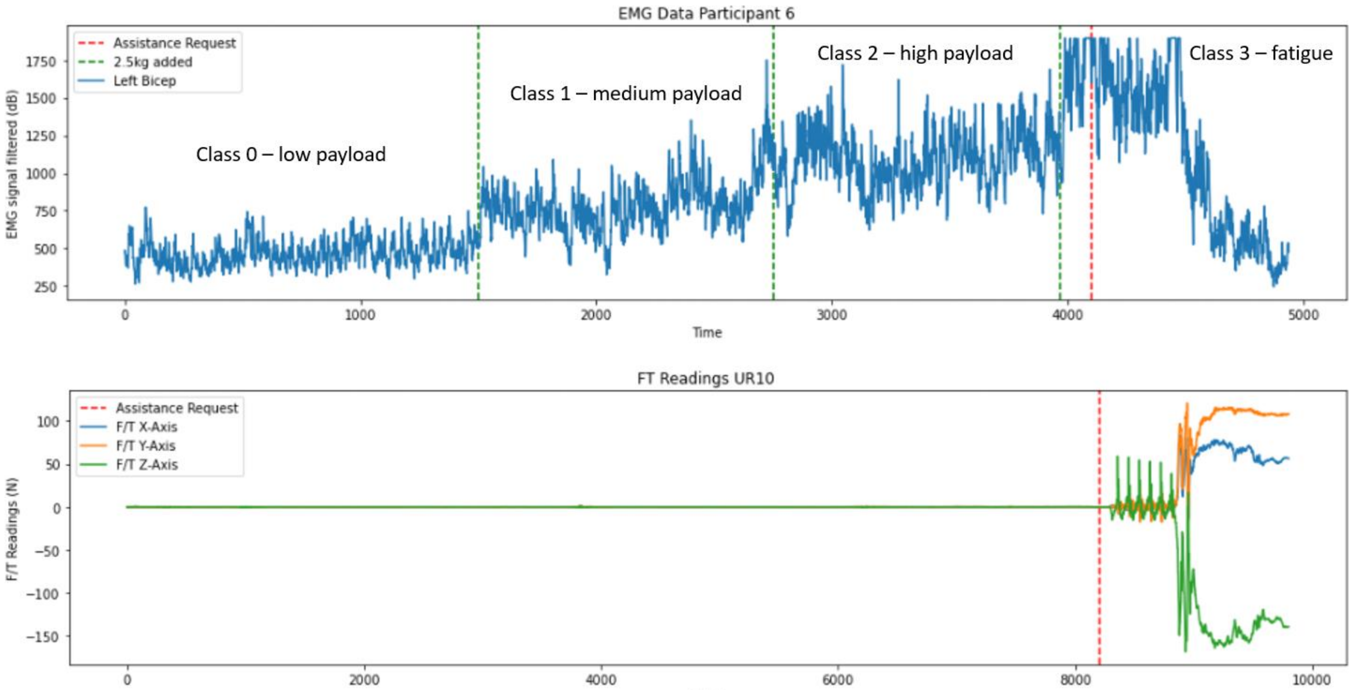

Fig. 5 Low bandpass filtered EMG data stream for the left bicep of participant 6, and synchronized force and torque readings (x,y,z axes) of the UR10. The green vertical lines in the EMG graph show the time when an additional 2.5kg weight was added. Thus, four payloads are distinguished from low until high/fatigued, when the assistance request was initiated (red vertical line). Note the units on the x-axis are based on the EMG sampling rate. The actual duration is ~75 seconds.

B. *Mondrian Forest Results*

Throughout the experiment EMG data was collected from 4 channels, namely the biceps brachii and the brachioradialis (forearm) for both left and right arm. Ideally, the classifier could predict the different payloads and the fatigue limit. This would allow for the classifier to trigger an assistance request, rather than a participant manually pushing a button. For this purpose, the bandpass filtered and STFT transformed EMG data was utilized to train and test a Mondrian Forest. Since the Mondrian Forest learns purely online, the collected data was streamed into the classifier in the same sampling rate as it was acquired (70Hz). Thus, this allowed for investigating the online learning capabilities regarding prediction performance and convergence time. One of the main challenges was to find an optimal number of trees, which delivered sufficient prediction accuracy, while minimizing convergence time. For evaluating the prediction performance, the metric Root Mean Square Error (RMSE) was chosen, since it provides an indication as close the predictions were, compared to the actual classification. For example, four different payloads can be distinguished for participant 6 (Fig. 5), classes 0 – "low payload" to 3 – "fatigued". If the classifier correctly predicted a window from class 3, the RMSE would be 0%. If, however, it predicted a window from class 3 as class 2, the RMSE would be 33%, as class 1 67%, and 100% if it predicted it as class 0 – "low payload" and so on.

TABLE II
MODEL TRAINED ON PARTICIPANT 6 AND TESTED ON ALL REMAINING PARTICIPANTS

Number of Trees	RMSE [%]	Convergence Time [ms]
1	81	29
5	65	165
7	64	268
10	47	459
11	48	521
12	52	613
13	36	483
14	41	421
15	29	459
16	26	487
17	**25**	**528**
18	28	570
19	34	613
20	27	632

As for the convergence time, the maximum time limit would be one STFT window size, which is currently 750ms. A longer period for classifying and learning would result in the classifier "lagging behind", meaning it could not classify new data fast enough, resulting in a continuously increasing queue.

In order to find the aforementioned optimum, a hyper-parameter optimization was performed based on a loop starting from 1 to 20 trees for each participant individually. However, in contrast to expected high prediction performances, the models did not deliver these results. In fact, whenever a new class was introduced, the model's performance went below 10% prediction accuracy for one or two seconds, until it correctly identified the new class. Consequently, due to the short observation window (2-3 minutes max) of EMG signals, the relatively poor performance rating would be misleading.

Instead, a so-called "warm start" was attempted, rather than training models from scratch. This included pre-training the model on one participant (also online), before applying it on other participants, as it would be faced in an authentic application. Sample results are shown in Table II, which presents the optimization scores of a model trained on participant 6 and then tested on all other participants. Participant 6 was chosen for the warm start, due to the average performance and subsequent number classes (4 different payloads, as shown in Fig. 5). As highlighted in Table II, the prediction accuracy reaches a saturation at 17 trees. After that, the prediction performance does not improve anymore. Thus, the optimum would be considered at an RMSE of 25% and 528ms convergence time. Generally, this accuracy is considered as acceptable, due to overlay in frequency/power of EMG signals during different predicted classes (classes 1 and 2 in Fig. 5). Regarding the convergence time, 528ms are below the set threshold of 750ms and therefore considered satisfactory. Overall, two factors need to be considered concerning the convergence time: hardware and code optimization. In the current setup, the Mondrian Forest was trained on a Linux Ubuntu 18.04 machine with an Intel Core i5 processor, NVIDIA NVS 5200M graphics card, 16GB RAM. Potentially lower convergence times would be anticipated with a stronger CPU. For code optimization, the Python 3.7 code was compiled into C through Cython. This substantially decreased convergence times from seconds to milliseconds.

After the general optimization, the “warm-started” model, trained on participant 6, was applied and further trained on each of the remaining participants individually. In this context, the goal was to investigate the uniqueness in features among individuals and subsequent potential differences in tree complexity. As shown in Table III, the data complexity and associated number of trees revealed similar results between different participants. In general, the optimum was reached at either 16 or 17 trees, suggesting similar levels of data complexity. The highest prediction performance was achieved for participant 7 at an RMSE of 7% The lowest performance was attained for participant 2 at an RMSE of 22% This could be due participant 2 having the longest recording and most different payloads (and subsequent classes), which would also result in the most diverse EMG signals. Nevertheless, the model could correctly predict the “fatigue limit” for participant 2 from the EMG data, as in when the participant pressed the assistance request button.

Overall, the Mondrian Forest achieved promising prediction accuracies, while keeping the convergence time below the set threshold of 750ms. As a side note, due to the Mondrian Forest generating the underlying trees randomly, it demonstrates a minor variation in terms of prediction performance and convergence time after each training.

TABLE III
MONDRIAN FOREST OPTIMUM FOR EACH PARTICIPANT

Participant	Number of Trees	RMSE [%]	Convergence Time [ms]
1	16 trees	16	472
2	16 trees	22	475
3	17 trees	10	498
4	17 trees	8	491
5	16 trees	11	472
6	-	-	-
7	17 trees	7	499
8	17 trees	10	492
9	16 trees	13	475
10	17 trees	8	498
11	17 trees	10	492
12	16 trees	9	473

VI. CONCLUSION AND FUTURE WORK

In this paper, a novel application of an Incremental Learner (Mondrian Forest) was proposed to predict payloads/muscular fatigue from EMG signals in Human-Robot Collaboration. This is envisioned to provide the collaborative system with awareness when an operator requires assistance from the robot. Since strength and endurance levels demonstrate a large variety among different individuals, the muscle activity and fatigue are directly measured on operator’s muscles. For this purpose, wearable EMG devices were placed on human operator’s biceps brachii and brachioradialis (forearm) since they are mainly involved in lifting/holding activities. However, other placements of EMG sensors are plausible, such as shoulder muscles and triceps (for pushing activities). Thus, this would allow for a wider range of scenarios regarding the prediction of payloads and associated fatigue levels.

In the current context, an experiment was performed, in which the payload held by participants was incrementally increased and the EMG data stream labelled, until they reached an uncomfortable/fatigued level. Participants then pressed an assistance request button, which triggered support of the collaborative robot. This data was used in the Mondrian Forest. At first, the acquired raw EMG data was streamed directly into the Mondrian Forest to minimize fine-tuning efforts. This, however, did not achieve sufficient results for all participants. Therefore, additional pre-processing steps were added in low bandpass filters and short-term Fourier Transform to extract relevant features (spectrum analysis). From this processed data the Mondrian Forest could identify the payloads and the fatigue threshold more accurately. Afterwards, a hyperparameter optimization of the Mondrian Forest could be performed regarding the number of trees in the model. Generally, the higher the number of trees, the higher the prediction performance, until a saturation is reached. After that threshold (so called elbow), the performance did not increase anymore. At the same time, a higher number of trees in the model results in a higher convergence time (time to perform a prediction and learning simultaneously). Thus, the optimization considered both: prediction performance and convergence time. Overall, promising prediction results were achieved, due to adaption of the models to the uniqueness of individuals. Moreover, since Incremental Learners purely learn online, this negates the effect of varying performances between offline and online applications. For instance, the Mondrian Forest correctly identified new classes (payloads) “on the fly”, without having seen the data before.

Limitations of the current setup were collaborative robot’s restricted maximum payload capabilities, which are often between 10-15kg. For instance, the UR10 used in the experiment has a maximum payload of 10kg. Consequently, the robot is fairly limited in terms of assisting operators with high payloads. On one hand, this maximum payload restriction is intended to create a safe collaborative working environment by protecting the health and safety of human operators. On the other hand, collaboration between humans and robots aims to compensate each party’s weakness, where human operators are considered susceptible to fatigue and robots are deemed fatigue proof. Hence, current collaborative robots would be required to evolve in terms of maximum payload, while maintaining safety for the human operator. Consequently, future research into safely coordinating higher levels of force/torque of cobots is considered necessary. Ultimately, this is envisioned to create a more ergonomic working environment, and thus, further synergetic effects between humans and robots.

VII. References

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