Machine Learning Physical Fatigue Estimation Approach Based on IMU and EMG Wearable Sensors

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Abstract

Physical fatigue refers to a state of exhaustion or reduced capacity for physical performance due to prolonged exertion, repetitive movements, or lack of rest. It is a multifaceted condition that can severely impact performance, especially in activities requiring sustained effort, precision, or concentration. In physical tasks, fatigue manifests as a decrease in muscle strength, coordination, and endurance, leading to diminished performance and an increased risk of injury. Detecting physical fatigue is crucial in a variety of domains: professional sports, collaborative robotics, construction, and more. This research introduces a novel framework for predicting fatigue during shoulder movements using data collected from wearable inertial measurement units and electromyography sensors. By integrating the Borg Scale, a subjective measure of perceived exertion, our approach uniquely combines objective sensor data with user-reported fatigue levels, creating a more holistic fatigue assessment model. The primary aim of this study is to develop a predictive model capable of accurately estimating fatigue, as measured by the Borg Scale. An investigation of the best machine learning algorithm for this task ensures that the chosen method provides the most reliable predictions. Furthermore, by systematically reducing the number of sensors and analyzing the impact on model performance, it is possible to find a minimal sensor configuration that maintains the model's predictive power while reducing complexity and cost. The Ridge Regression model, after hyperparameter tuning, outperformed other models, achieving a mean absolute error of 2.417 in predicting fatigue. This preliminary study shows the potential of integrating data from different inertial and electromyography sensors for fatigue prediction in shoulder movements, with potential applications in occupational safety.

Keywords

Fatigue Estimation, Wearable Sensors, Machine Learning, Feature Selection

1. Introduction

Muscular fatigue is a critical factor influencing performance, safety, and recovery in a wide range of activities, from athletic training to industrial work and rehabilitation. Repeated or sustained physical exertion can lead to overuse and fatigue in specific muscle groups, particularly those involved in repetitive or high-intensity movements. Shoulder joint fatigue, in particular, is of great concern due to the central role it plays in numerous sports, occupational tasks, and rehabilitation exercises [1, 2]. Activities such as tennis serves, golf swings, swimming strokes, and overhead throwing place significant demands on the shoulder muscles, making them highly susceptible to fatigue [3, 4]. In work environments, tasks like lifting, assembling, and pulling often require prolonged or repetitive shoulder movements, increasing the risk of fatigue-induced musculoskeletal disorders [5]. Likewise, in rehabilitation, managing fatigue is crucial for developing safe, progressive exercise programs that facilitate muscle recovery and prevent overstrain.

The ability to accurately monitor and assess physical fatigue during shoulder movements is essential for optimizing performance, preventing injury, and improving recovery outcomes. Traditional methods of fatigue monitoring rely heavily on subjective reporting or periodic physical evaluations, but these approaches are often limited by their inability to capture real-time changes in muscle performance and

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fatigue progression. Advances in wearable technology, however, now offer an objective and continuous means of monitoring fatigue. Wearable sensors such as Inertial Measurement Units (IMUs) and surface Electromyography (EMG) enable real-time tracking of biomechanical and physiological data, providing a more comprehensive understanding of how fatigue develops over time[6]. EMG is a technique that measures the electrical activity produced by muscles during contraction, providing insights into muscle activation and overall function. IMUs are sensors that track motion and orientation using accelerometers, gyroscopes, and sometimes magnetometers, capturing detailed kinematic data during physical activities. IMUs and sEMG sensors are essential for capturing detailed biomechanical and muscle activity data in fatigue prediction [7, 8]. This integration offers a holistic view of physiological states, enhancing prediction accuracy. The combined use of IMU and EMG sensors provides deeper insights into fatigue development across different muscles and activities, proving beneficial for real-time monitoring in sports and rehabilitation contexts.

This study aims to address the current gap in fatigue monitoring by providing a comprehensive approach that includes both objective sensor data and subjective fatigue assessments during shoulder internal rotation and external rotation exercises under varying load conditions. By analyzing the relationship between muscle activity, motion patterns, and physiological responses, this work seeks to develop a robust fatigue prediction model that can be applied in sports, occupational settings, and rehabilitation. Furthermore, the dataset supports the development of machine learning algorithms for real-time fatigue detection, ultimately contributing to improved performance management, injury prevention, and workplace ergonomics.

2. Literature Review

Wearable sensors are small, non-invasive devices that can measure a range of physiological signals, such as muscle activity, heart rate, and movement patterns. The data collected from these sensors is often time series data, which captures the dynamic changes in physiological parameters over time. This data can then be analyzed using various predictive models to estimate the onset and progression of fatigue during physical activities. In sports science, accurately predicting fatigue is crucial for optimizing performance and preventing injuries. Fatigue can affect an athlete's technique, reaction time, and overall performance, making monitoring fatigue levels during training and competition essential. Wearable sensors have been widely used to monitor athletes in real time, providing data that can be analyzed to detect early signs of fatigue. One study by [9] utilized IMU data collected from athletes performing running exercises to predict muscle fatigue. The IMU sensor was attached to their wrist. The researchers applied a machine learning approach using models such as Linear Regression with Elastic Net regularization (EN) and Linear Regression with Least Absolute Shrinkage and Selection Operator regularization (LASSO) to predict the rating of perceived exertion (RPE) based on the IMU signals. The study demonstrated that machine learning models could accurately predict fatigue, providing a valuable tool for coaches and trainers to manage athlete workload and prevent overtraining. Similarly, a study by [10] explored the use of IMUs to analyze complex datasets, bringing innovation to the monitoring and optimization of athlete training cycles. The raw time series data were used to train a supervised machine learning model based on frequency and time-domain characteristics. The model was able to forecast the beginning of fatigue before any physical symptoms appeared, highlighting the potential of wearable sensors in sports performance optimization. The model demonstrated that timely interventions could prevent overtraining and potential accidents. Additionally, the study demonstrated the model‘s efficacy in real-time monitoring, improving the decision-making abilities of both coaches and athletes. Another notable study by [11] developed an intelligent sports fatigue prediction system based on spectral sensors and machine learning algorithms. This system was particularly effective in handling the nonlinearities associated with physiological data during sports activities, offering a robust solution for predicting the degree of fatigue in athletes. These studies highlight the importance of integrating advanced machine learning techniques with wearable sensor data to create predictive models that can accurately assess and manage fatigue in sports contexts.

Wearable sensors are vital in physical rehabilitation, as they continuously monitor patients during recovery exercises. Pinto-Bernal et al. focused on fatigue management during walking tasks using IMUs and sEMG sensors, developing a random forest model that classified fatigue into four states with high accuracy. This tool is essential for customizing rehabilitation programs [8]. Additionally, EMG and accelerometer signals have been used for predicting whole-body fatigue, showcasing the ability of wearable sensors to provide real-time feedback and assist clinicians in adjusting therapy intensity [7]. The work describes the

In industrial applications, wearable sensors are effective for predicting fatigue and enhancing workplace safety and productivity. Kuber et al. developed a fatigue prediction model using EMG and IMUs in workers wearing back-support exoskeletons during trunk-flexion tasks [12]. They applied machine learning algorithms like SVM, Random Forest, and XGBoost, achieving up to 95% accuracy with combined sensor data. This study underscores the potential of wearable technology in monitoring fatigue and improving ergonomic practices in demanding jobs.

In the context of fatigue prediction, IMU and EMG sensors are particularly useful due to their ability to capture detailed biomechanical and muscle activity data. These sensors complement each other; IMUs track movement dynamics, while sEMG records muscle activation patterns, making them highly effective in identifying fatigue. For instance, the study by [7] utilized a combination of EMG and IMU data to monitor fatigue in real-time during rehabilitation exercises. By integrating data from these sensors, the researchers could assess muscle fatigue more accurately, which is crucial for preventing overexertion during recovery tasks. Similarly, [8] employed both EMG and IMUs in their study on fatigue management during rehabilitation. Their approach involved using these sensors to gather comprehensive data on muscle activity and movement, which was then processed using machine learning algorithms to classify different fatigue states. This method proved highly effective, as the combination of EMG and IMU data provided a more holistic view of the patient's physiological states, leading to more accurate fatigue prediction. This combined approach is particularly beneficial in applications requiring real-time monitoring and feedback, such as in sports and rehabilitation settings. However, their approach tackled it as a classification problem, providing less detailed prediction compared to a regression task.

3. Dataset Preparation

This section describes the dataset used and the methodology used to preprocess it. This study is based on the measurements collected by Yasar et al. [13]. The data collection took place at the Tyndall National Institute's Wearable Laboratory, University College Cork, in Cork, Ireland, between April and July 2023. The research was conducted on 34 healthy individuals, of which 23 were male and 11 were female. All 34 subjects had no previous history of musculoskeletal injuries. All the participants were physically active and engaged in some form of physical training at least thrice a week.

To evaluate muscle activation and upper extremity movements, EMG electrodes and IMU sensors were applied to the dominant side of the upper body following the warm-up. A wireless EMG system with a 1000 Hz sampling frequency was used to capture muscle activation. The reference areas indicated in Cram's Introduction to Surface Electromyography [14] were followed while positioning the EMG electrodes. IMU sensors were placed on the hand, forearm, upper arm, shoulder, sternum, and pelvis. A push/pull dynamometer was used to measure the volunteer's greatest Voluntary Isometric Contraction forces during shoulder internal rotation and external rotation movements in order to determine the greatest force the muscles can exert without changing their length. Every measurement had a duration of five seconds and was conducted twice every two minutes. Participants in the MVIC assessment were sitting on a bench, pulling a dynamometer that was clamped to a table next to them, with their wrists straight and elbows bent 90 degrees. For analysis, the mean of the two consecutive force measurements was employed. After that, participants used cable pulley equipment to repeat shoulder internal rotation and external rotation motions in a random order using 30 - 40% of their MVIC force. There was a 10-minute break in between each measurement. While standing, subjects were positioned laterally to the fixed cable pulley, elbow flexed at a 90-degree angle, and wrist straight for the shoulder's internal and external rotation movements, as shown in Figure ??.

The Borg RPE scale was used to gauge each participant's felt state of physical exhaustion before and during shoulder internal rotation and external rotation movements, as well as every 10 seconds. The Borg RPE scale describes "no exertion at all" to "maximum exertion" and has a range of 6 to 20. It enables people to gauge how hard a task is and how tired they are. The exercise was continued until the subject was unable to exert any more effort (level 20). During the tests, a metronome set at 40 beats per minute was utilized to guarantee that the workouts were performed at a steady pace. For more details, the original dataset paper is publicly available [13].

3.1. Data Pre-processing

This section describes the procedure to prepare the collected dataset into a format suitable for a supervised machine learning task. Established literature shows that a band-pass filter effectively eliminates motion artefacts in EMG signals. Increasing the cut-off frequency reduces ECG contamination and smooths the signal, concluding that a high-pass filter with a cut-off of around 30 Hz is optimal. For the EMG, the mean is subtracted from the signal, and a 4th-order Butterworth band-pass filter has been applied with a low cut-off at 30 Hz and a high cut-off at 350 Hz [15]. To segment the continuous EMG and IMU signals into the different repetitions, EMG and IMU data were segmented by identifying the relevant peaks and delimitating their beginning/end. For internal rotation movements, repetitions were defined as segments between two successive zero-crossing points. For external rotation, they were defined between a peak and the subsequent valley. This method ensured accurate segmentation for both movements.

The Borg scale ratings, a self-assessment metric of perceived exertion, have to be assigned to each individual data repetition. The Borg scale was recorded at 10-second intervals during the exercises. Since repetitions occurring between assessments lacked corresponding Borg values, these values had to be inferred using linear interpolation of the known Borg values. The time for each repetition was cumulatively summed, and ratings were mapped directly based on the nearest recorded values. The interpolated Borg ratings, starting at 6 and ending at 20, were stored and used as targets of the machine learning task. Any samples exceeding the final Borg recording time by 10 seconds were excluded to avoid inaccuracies.

3.2. Feature Extraction

Feature extraction is fundamental to avoid overfitting due to the high dimensionality and limited amount of individuals. This process transforms raw data into representative features for analysis and modelling. The goal is to reduce data dimensionality while retaining essential information. The TSFEL package has been used to automatically extract features from time series data, encompassing statistical, temporal, and frequency domains. It simplifies the extraction process, ensuring a diverse feature set for analysis [16]. After segmenting the EMG and IMU data, features were extracted using a window size of 30 samples with a 10-sample overlap for EMG and 300 samples with a 100-sample overlap for IMU. This approach effectively captured fine details in EMG and broader motion patterns in IMU data.

4. Methodology

The problem is a supervised regression task. Given all the signals collected by the sensors from a single repetition, predict the Borg level. The preprocessed dataset described in the previous section is fed to a machine learning pipeline composed of a min-max scaler, Principal Component Analysis (PCA) dimensionality reduction, Recursive Feature Elimination (RFE) and finally, the chosen regressor.

A large number of features were generated after feature extraction, leading to redundancy and collinearity. Dimensionality reduction reduces the number of input variables while retaining relevant information, simplifying interpretation and analysis. For these reasons, the feature space has been reduced by deploying PCA. PCA is one of the most widely used dimensionality reduction techniques. It identifies orthonormal vectors that explain the variance structure of the data, aiming to find the most meaningful basis to re-express a dataset and filter out noise to reveal hidden structures. While RFE is a feature selection method that iteratively reduces the number of features to identify the most important ones. It works by training an estimator on the full set of features, ranking them based on their importance. The least important features are removed, and the process is repeated on the reduced feature set until the desired number of features is selected.

The following machine learning regressors have been considered due to their good performances in similar tasks:

- **Random Forest Regressor**: is an ensemble learning algorithm used for regression tasks, predicting continuous values by using a bagging technique (Bootstrap Aggregating).
- **Lasso Regression**: applies L1 regularization, which forces some coefficients to be exactly zero, effectively performing feature selection and reducing overfitting.
- **Ridge Regression**: incorporates L2 regularization, adding the squared magnitude of coefficients to the loss function, which helps prevent overfitting, especially in datasets with many features or multicollinearity.
- **Elastic Net**: is a hybrid of Lasso and Ridge regressions, combining both L1 and L2 penalties to balance model complexity and improve predictive accuracy, particularly in datasets with correlated features.

The dataset's particularity requires a custom cross-validation approach to avoid data leakage. The folds have been designed to group together all the repetitions of an individual, avoiding the presence of data from a person in both the train and test sets. A leave-one-out approach at the subject level has been used in this case. This created 34 models, each tested in a participant after being trained in all the data from the other subjects. The best parameters for PCA (number of components) and the regressors have been selected through an extensive hyperparametrisation procedure using grid search.

4.1. Sensor Reduction Procedure

The dataset analysed comprised 12 sensors, requiring a complex setup that might be quite uncomfortable for the subject. For instance, in sports involving physical activity, sensors placed on different parts of a player's body could restrict movement, cause irritation, or even affect the athlete's natural performance. This raises important considerations regarding the practicality and feasibility of deploying such a comprehensive sensor array in real-world situations. The volume of data generated from these 12 sensors could present challenges in data storage and processing and in real-time analysis. Reducing the number of sensors used to predict fatigue levels would lead to smaller, cheaper, and more comfortable devices with longer charge life. For these reasons, a procedure to identify an efficient set of sensors is crucial for the application. Once a sensor is added to the design, there is no additional cost to leverage all the features provided by that sensor. Traditional feature selection does not consider this aspect. Potentially, some sensors are not contributing to fatigue detection, or their impact can be inferred from the other sensors, making them redundant. Evaluating all possible sensor combinations would require an exponential number of models, 2^{12} in this case, making it unfeasible in reality. For this reason, an iterative backward sensor elimination procedure has been devised. Starting from the full set of sensors, the procedure iteratively eliminated the sensor that has the least impact in terms of accuracy. Given a set of n remaining sensors, the procedure applied is the following:

1. Create n models, each trained on a dataset obtained by removing all data from a sensor.
2. Evaluate each model and select the one with the higher accuracy. That model is the one that has been the least affected by the sensor removal.
3. Remove from the dataset the sensor with the least impact.
4. Iterate the procedure with $n - 1$ sensor unless only one sensor is remaining.

In this case, the number of models evaluated is the triangular number of the number of sensors (78 starting with 12 sensors). While this is not guaranteed to provide the best subset, it can be computer in a reasonable time.

4.2. Metrics

All models have been compared in terms of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The MSE measures the average squared prediction error, emphasizing larger errors due to its sensitivity to outliers. The RMSE is the square root of MSE, providing an interpretable error metric in the same units as the target variable while maintaining sensitivity to large errors. The MAE calculates the average absolute difference between predicted and actual values, treating all errors equally and making it more robust against outliers. Finally, the MAPE expresses the error as a percentage of the actual values by averaging the absolute percentage differences between predicted and actual values. It provides an intuitive measure of prediction accuracy but can be distorted by very small actual values, leading to large percentage errors.

5. Experimental Results

The function of this section is to present the experimental study. In Section The research was conducted using Python. The code and preprocessed datasets are made publicly available[1].

5.1. All Sensors

This experiment evaluated the potential to predict the Borg scale with different regressors using data from all the sensors available. Due to the lack of a comparable approach in the literature, a simple mean baseline has been considered. This baseline predicted the average Borg value of the training set. Its goal was to assess if the regressors can extrapolate information relative to the fatigue from the sensors or are only learning the distribution of the training labels.

Table 1
Regressors performance sort by MSE.

Model	MSE	MAE	MAPE	RMSE
Ridge	8.639	2.417	0.199	2.972
Lasso	8.897	2.490	0.203	3.029
ElasticNet	8.705	2.430	0.200	2.979
RandomForestRegressor	9.819	2.561	0.214	3.240
Baseline	15.275	3.338	0.264	3.936

Table 1 shows the regression results. All models can strongly outperform a simple baseline, showing that the sensors provide useful information on fatigue that is transferable across different persons. On average, the baseline model has 3.4 points of difference from the self-assessed Borg, while the best model has only a 2.4 difference. Considering the fact that the perception of physical fatigue is subjective, that the Borg scale is a self-assessment, and that the values have been linearly interpolated, the result is particularly promising.

The best model is the Ridge regressor, whose performance is shown in Figure 1. Closer a point is to the red dotted line, more accurate the prediction is. A stronger density around the line confirms that part of the patterns learned from the model are correlated to physical fatigue. Ridge Regression's ability to perform well across all metrics suggests that it strikes a good balance between bias and variance, making it the most reliable model in this context.

[1]https://github.com/andvise/FatigueEstimation

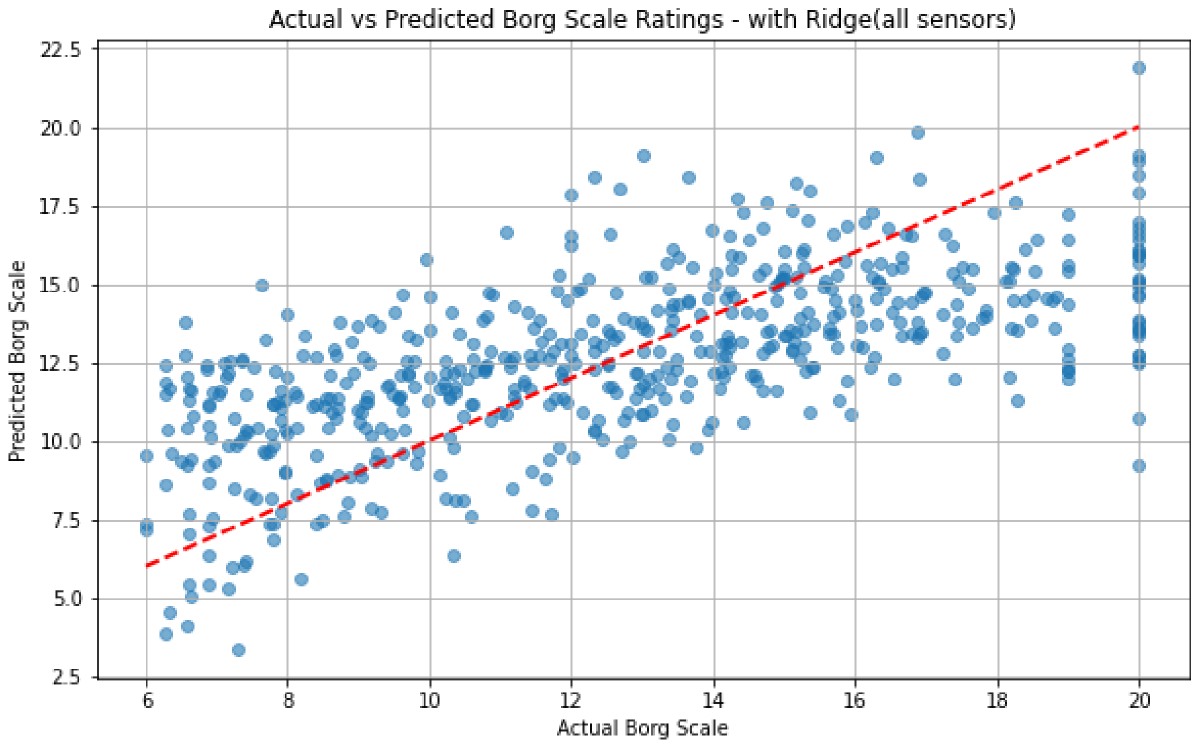

Figure 1: Ridge Regression (all sensors included)

The Random Forest Regressor is the least effective machine learning model in this comparison. It has the highest MAE (2.561), which means its predictions are, on average, the furthest from the actual values compared to the other models. The poorer performance of the Random Forest Regressor may be due to its complexity or the possibility that it is not as well-suited to the specific characteristics of this dataset as the linear models. The patterns learned are likely overfitting and poorly translated to an unseen subject. Figure 2 shows the model's predictions. Compared to the Ridge Regressor, the dots are more sparse and distributed across the plot. Due to its superior performance and for the sake of brevity, the next sections focus on the Ridge Regression model.

5.2. IMU and EMG Sensor Data Comparison

Two Ridge models have been tested on all IMU or EMG sensor datasets. The analysis provides an overview of which type of sensor provide more relevant patterns for fatigue estimation. The results of the evaluation are given in Table 2.

Table 2
Performance Metrics for Models Using IMU Only and EMG Only Sensor Data

Sensor	MSE	MAE	MAPE	RMSE
IMU only	11.706	2.821	0.236	3.470
EMG only	13.719	3.122	0.262	3.835

The overall performance considerably worsens with only one type of sensor. The IMU-only model outperforms the EMG-based one. However, its accuracy is considerably worse than the Random Forest Regression in Table 1, the model with the lowest accuracy. The effect can be seen in Figure 3; the model is more conservative with the predictions, avoiding outputting high or low values. The performance of the EMG-only data is surprisingly inaccurate. The EMG is considered an effective sensor for measuring fatigue [17]. In this particular case, the full set performs only slightly above the chance level.

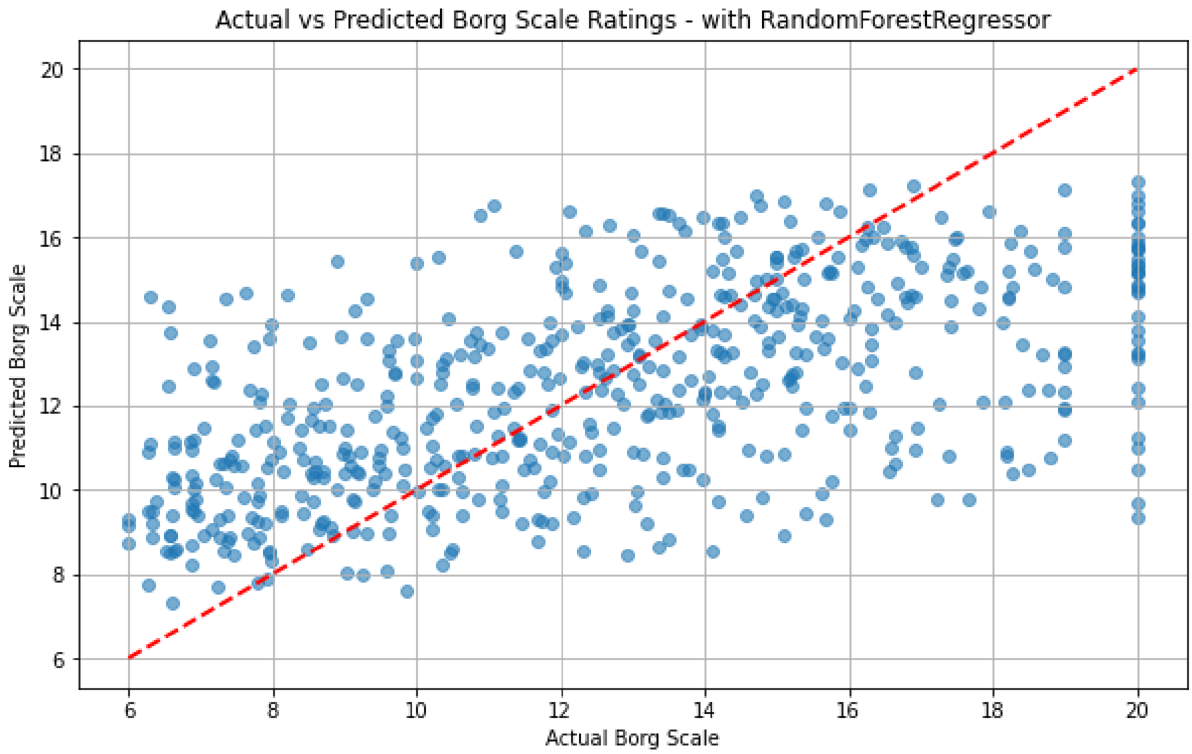

Figure 2: Random Forest Regressor (all sensors included)

When both IMU and EMG data were integrated, the combined model from the previous section achieved an MSE of 8.639, which is notably lower than the MSEs of both the IMU-only and EMG-only models. These results clearly indicate that integrating both IMU and EMG data leads to a more accurate and reliable model, leveraging the complementary strengths of each sensor type to enhance the overall predictive performance.

5.3. Individual Sensor Comparison

The set of 12 sensors is distributed across the body, and their connectivity requires a bulky device. Wearing multiple sensors during physical activity could restrict movement, cause irritation, or even affect the athlete's natural performance. This raises important considerations regarding the practicality and feasibility of deploying such a comprehensive sensor array in real-world situations. This experiment evaluates the performance of the Ridge Regressor on data collected from a single sensor.

Table 3 presents the accuracy of the model trained on individual sensors specifying their location. In contrast with the previous section, the individual EMG sensors are the most accurate ones, outperforming the set containing all EMG sensors. This could be caused by the fact that the high dimensionality of the data leads to patterns that are not representative of the real phenomena. However, all models trained on a single sensor are less accurate than the ones trained on the full dataset. The location of the most relevant sensors is consistent with the biomechanical movement. The infraspinatus is one of the four muscles of the rotator cuff; its main role is to rotate the humerus and stabilize the shoulder. While the pectoralis major is the largest muscle of the frontal chest. Both of them are widely involved in the two rotation movements.

5.4. Backward Sensor Elimination

The previous experiments showed that while some individual sensors yielded relatively good MSE results, they still fell short of the model's performance using all sensors. This indicates that relying on a

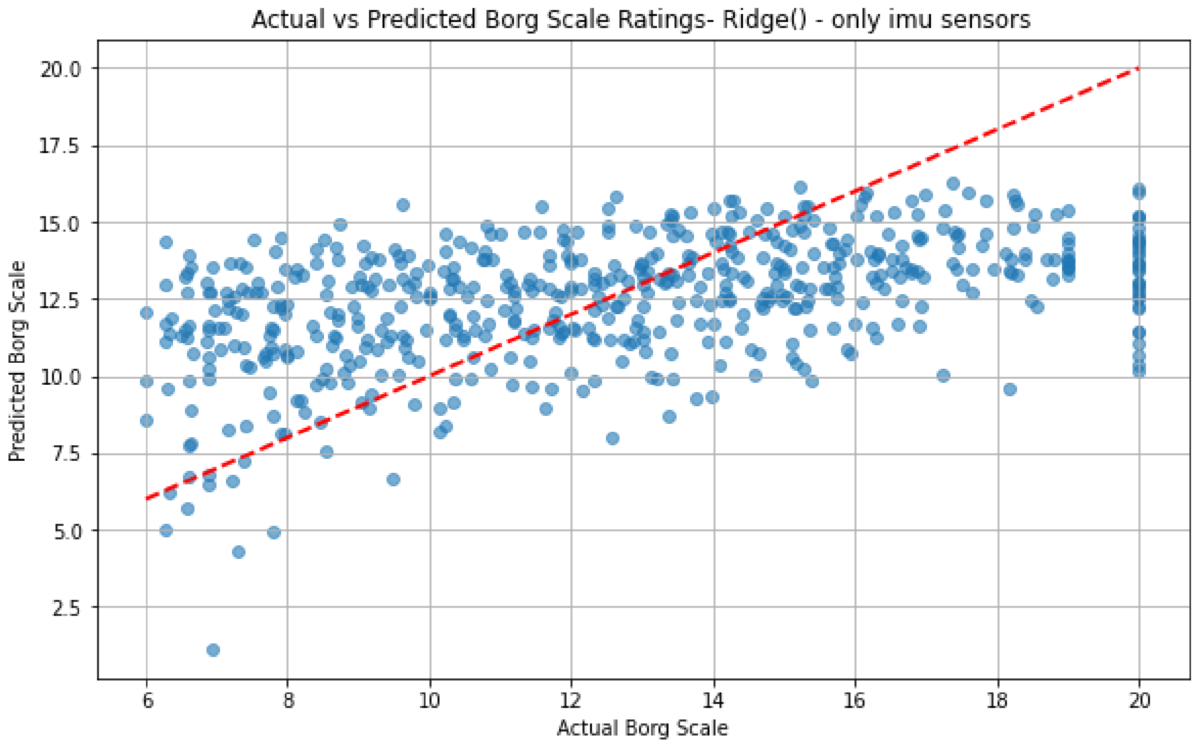

Figure 3: Ridge Regressor (IMU sensors only)

Table 3
Model accuracy by MSE for sensors positioned in various locations.

Sensor	Muscle	MSE	MAE
EMG	infraspinatus	11.578	2.848
EMG	pectoralis_major	12.340	2.845
EMG	deltoidus_anterior	13.751	3.036
IMU	upper_arm	13.670	3.052
EMG	deltoidus_posterior	13.848	3.148
IMU	palm	13.824	3.141
IMU	pelvis	13.773	3.097
IMU	torso	13.423	3.071
EMG	trapezius_ascendens	13.840	3.136
IMU	shoulder	14.157	3.023
EMG	latissimus_dorsi	14.021	3.166
IMU	forearm	14.512	3.155

single sensor is insufficient for accurately predicting outcomes in complex tasks like shoulder rotation exercises. However, some of the individual sensors might be sampling areas that are not involved in the movement or are redundant. The aim of this section is to identify a set of sensors that provide accuracy comparable to the complete data. The procedure described in Section 4.1 is used for this goal.

Figure 4 shows the decrease of the MAE over the increase of the number of sensors. The horizontal axis contains the sensor removed at each step. The rightmost point represents the accuracy of the full dataset. The first sensor was discarded in the EMG on the trapezius ascendes. The process is iterated until the EMG sensor on the pectoralis major is removed, leaving only the one on the infraspinatus that alone reaches an MSE of 2.93 (since that sensor has not been removed, it is not present in the horizontal axis labels). As expected, the progressive reduction of sensors leads to an increase in the model's accuracy.

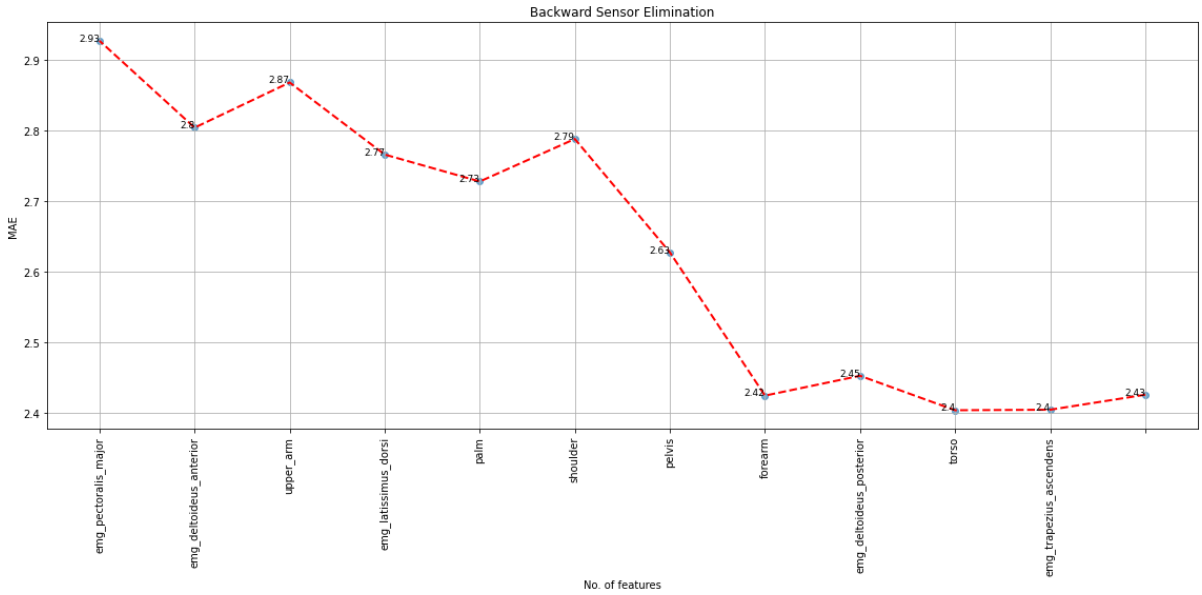

Figure 4: Features used against the change in MAE. The last sensor remaining is the infraspinatus EMG.

Notably, the error increases significantly after removing the pelvis and shoulder IMU sensors. In line with the previous results, infraspinatus, pectoralis major and deltoideus anterior are the last ones to be removed. This is due to their role in stabilizing the shoulder during external rotation, making them sensitive to fatigue. The palm and upper arm IMUs could reflect a change in posture or movement due to the overall muscle fatigue, effectively capturing key activities in shoulder external rotation. The analysis indicates that removing the forearm and torso IMUs, and the deltoideus posterior and trapezius ascendens would likely not impact the accuracy of the model. This would allow a simplification of the sensors that does not impact the performance.

6. Conclusions

This study aligns with research highlighting the usefulness of IMU and EMG sensors for tracking physiological and biomechanical characteristics. Similar studies have demonstrated their utility across various fields, including sports science, occupational health, and rehabilitation. However, predicting the Borg scale value is a challenging task due to the subjective nature of physical fatigue perception and the uncertainty caused by the self-assessment. The proposed data preprocessing and machine learning pipeline demonstrated the potential in predicting the perceived fatigue in individual previously unseen. The importance of both the mechanical aspect of the movement assessed by the IMUs and the muscular electrical activity measured by the EMGs has been highlighted since the best models require both sensors. Finally, a procedure to obtain a reduced set of sensors by iteratively removing the least impacting one provided a smaller set of sensors with equivalent accuracy. Opening the path for the development of cheaper, lighter and more efficient tools. This work underscores advancements in machine learning algorithms and sensor technologies, enhancing our understanding and application of these instruments for real-time fatigue evaluation.

While significant findings were achieved, the study had limitations. The primary limitation was the relatively small sample size, which may restrict the generalizability of the results and the accuracy of the models. The high dimensionality and the small population size lead to the creation of various patterns that are not related to fatigue. Additionally, the focus on healthy adults may not translate to populations with musculoskeletal disorders or athletes with different fatigue dynamics. However, the procedures developed herein and their implementation can be easily adapted to the new dataset collected. Finally, the addition of explainability approaches would provide a more informative picture to practitioners [18].

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