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Developing a Novel Fatigue Index: Metrics and Regression Modeling for sEMG-Based Muscle Fatigue Analysis

Introduction

Muscle fatigue is a critical physiological phenomenon, impacting performance in sports, rehabilitation, and daily activities. Surface electromyography (sEMG) signals are widely used to monitor muscle activity and have shown potential in evaluating fatigue. However, existing methods often rely on indirect or predefined fatigue indicators, limiting their ability to provide a comprehensive measure of fatigue progression.

In this study, we present a two-fold approach to advance the understanding and measurement of muscle fatigue:

1. **Metric Evaluation**: We collected sEMG data from multiple participants performing sustained muscle contractions under continuous fatigue. From this data, we identified and validated time-domain, frequency-domain and combined-domain metrics that reliably correlate with fatigue progression.
2. **Regression Modeling**: Recognizing the absence of a direct measure of fatigue, we explored regression techniques to develop a new fatigue index. By testing different hypothetical fatigue trends over time, we trained models to approximate these trends using the identified metrics, achieving a robust representation of fatigue progression.

This work not only identifies key fatigue-related metrics but also introduces a novel method to quantify fatigue trends, paving the way for more precise applications in monitoring and managing muscle fatigue.

Table of Contents

Introduction 1

1. Measurement and Metric Evaluation 3

1. Objective 3

2. Experimental Setup 3

3. Data Collection 5

4. Metric Analysis 5

1. MNF/ARV ratio 5

2. Instantaneous Mean Amplitude difference of High and Low Frequency component 7

3. Multifractal Detrended Moving Average (MFDMA) 9

4. Empirical Mode Decomposition and Intrinsic Mode Functions 11

5. Scaled Fluctuations and Range, Variance, Mean Abs Differences and Entropy 12

2. Regression Modeling for Fatigue Index Creation 13

1. Objective 13

2. Regression Model Development 13

3. Training and Validation 13

4. Outcome 13

1. Measurement and Metric Evaluation

1. Objective

To measure sEMG signals from multiple participants while their muscle was under continuous fatigue and identify custom metrics that correlate strongly with fatigue levels.

2. Experimental Setup

The measurement process consists 3 phases:

1. The rest phase at first for some seconds, then
2. The activation phase, when the participant extends his leg to maintain a stable position for the isometric contraction and ultimately
3. The active phase, when the leg remains extended for almost a minute.

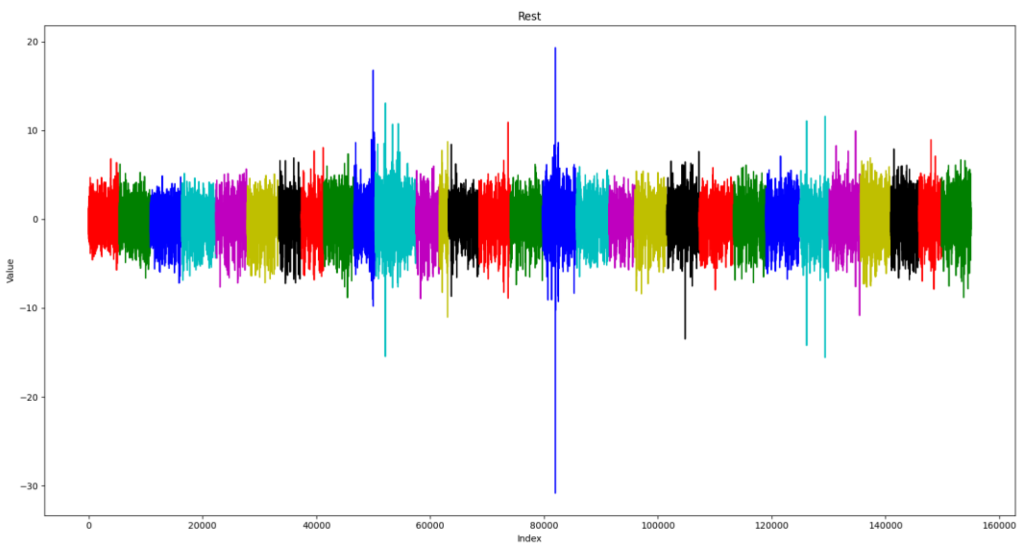


Figure 1: Rest phase side by side for multiple participants

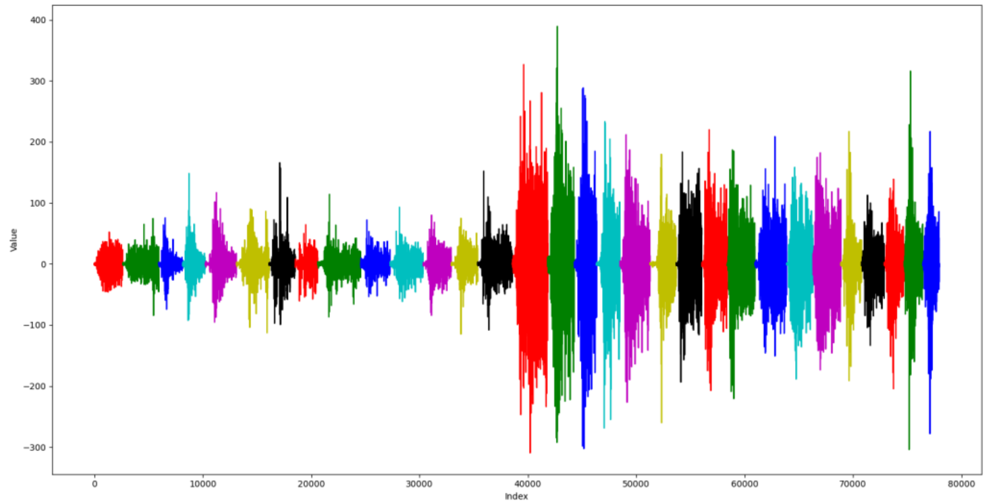


Figure 2: Activation phase side by side for multiple participants

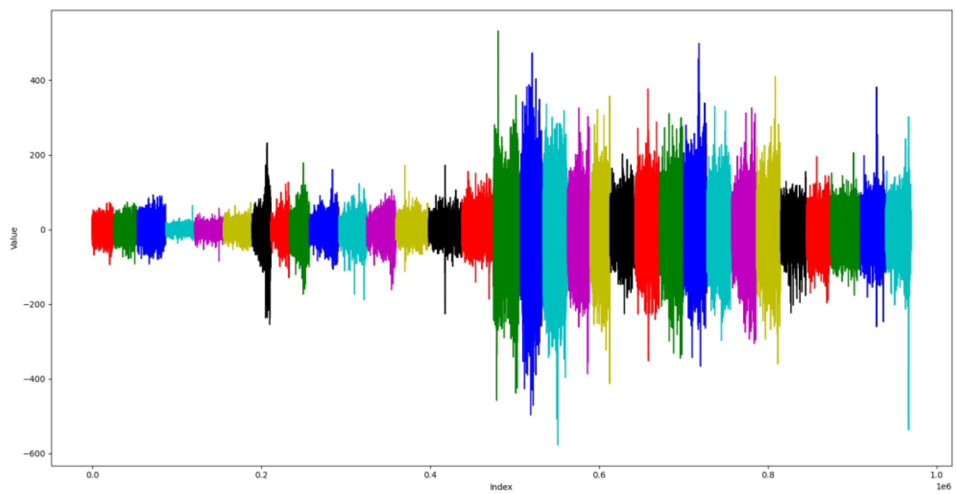


Figure 3: Active phase side by side for multiple participants

3. Data Collection

The sEMG signal is processed using a 4th-order band-pass Butterworth IIR filter implemented as cascaded second-order sections (biquads). This filter isolates the frequency range of 25 Hz to 380 Hz, which corresponds to typical sEMG activity, while suppressing noise outside this range.

The 50Hz is eliminated because in the experiment, the custom sEMG device was being powered with a powerbank of 5V output.

4. Metric Analysis

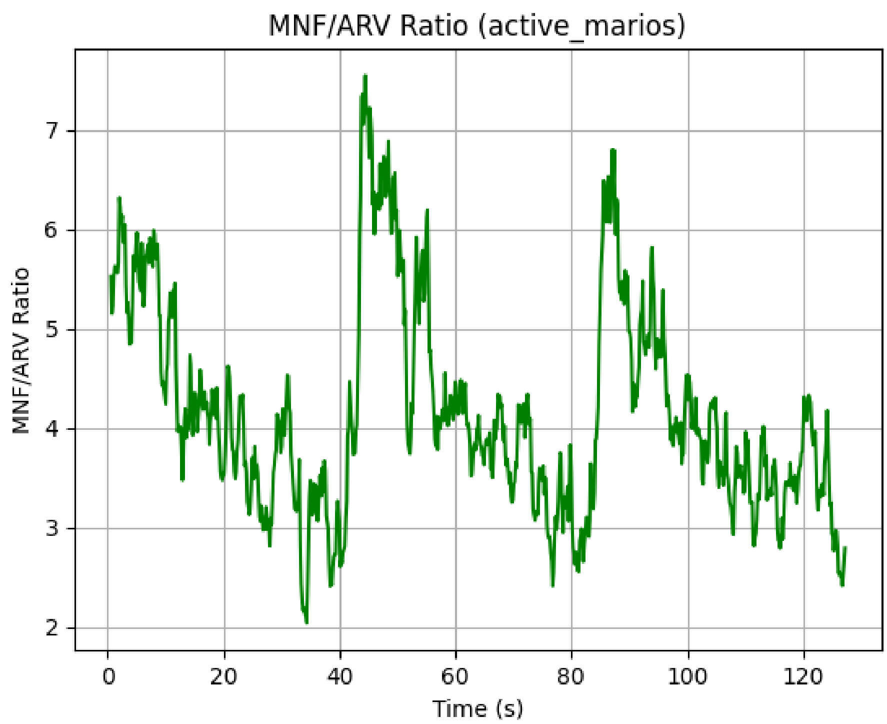
During the implementation of the thesis, the basic metrics used to extract conclusions where RMS, Integrated EMG, Mean Frequency and Median Power Frequency. While these metrics are very promising, when used alone they cannot provide very meaningful results regarding the progression of fatigue but only for the existence of the fatigue. Meanwhile, when using a fusion of metrics things can become more interesting.

While studying additional bibliography, these parts are interesting:

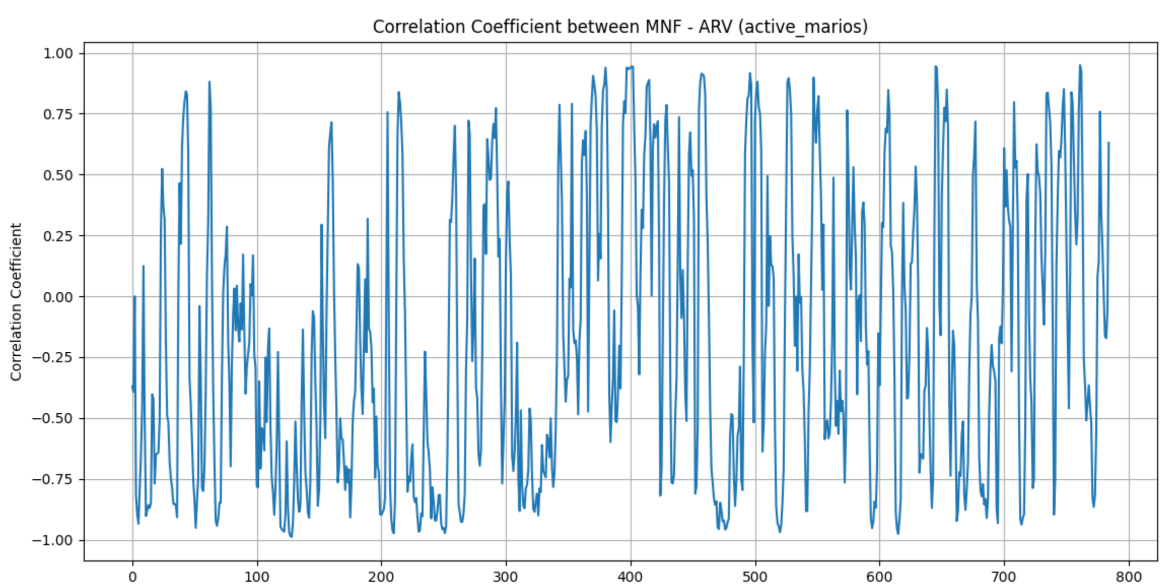
1. MNF/ARV ratio

The **MNF/ARV ratio** (https://ieeexplore.ieee.org/document/7591924) is calculated and regarded as an index of muscle fatigue, where **the ratio gradually decreases as fatigue progresses**. Fatigue exists once the ratio reaches a specific baseline, which is defined as the inverse value of the MNF/ARV. As reported by the authors, the initial values of the MNF and ARV (Absolute Rectified Value) are taken as the reference values for the baseline to eliminate individual differences.
The **correlation coefficient** between MNF and ARV is taken as an index of fatigue. The **conversion** of the correlation coefficient **from positive to negative** is regarded as a sign of muscle fatigue. However, to calculate correlation coefficient stably requires a long interval, which generates delay in the estimation. If the interval is shortened, the correlation coefficient may fluctuate between positive and negative. Moreover, the correlation coefficient for non-fatigued muscle may also decrease, and thus become indistinguishable with fatigued muscle.

Below, there are the plots of the MNF/ARV ratio which as mentioned in the bibliography it gradually decreases as fatigue progresses. It contains 3 sessions presented side by side.



Also, the plots of the correlation efficient, leading to uncertain conclusions, as mentioned above.

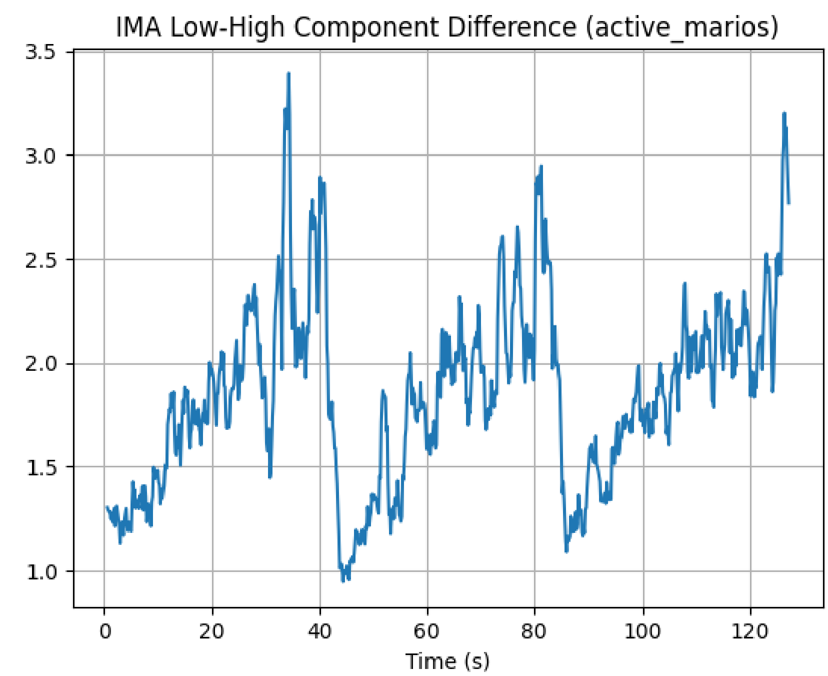


2. Instantaneous Mean Amplitude difference of High and Low Frequency component

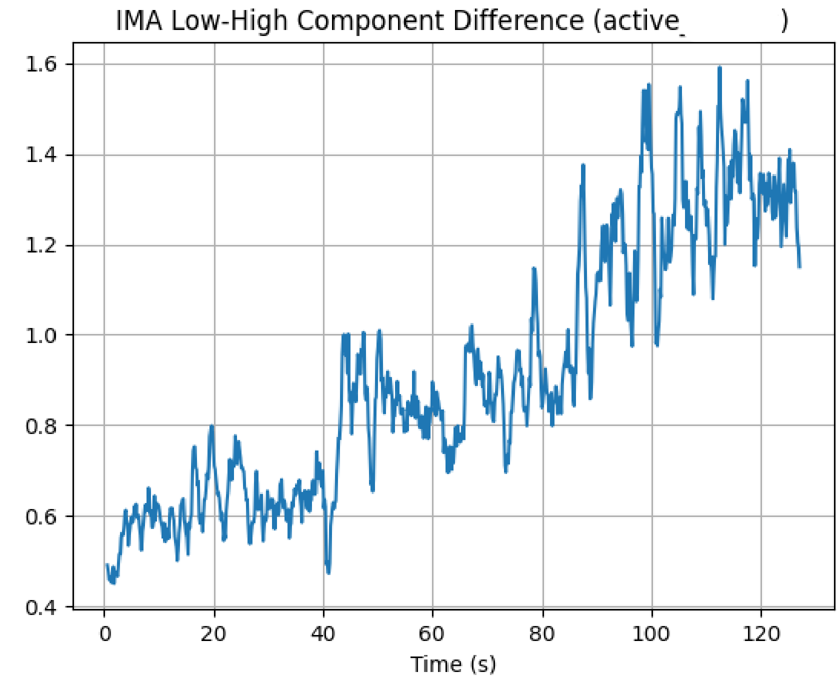
The second metric evaluated is the one extracted from Algorithm B during the thesis (https://doi.org/10.3390/s22051900) but improved. This algorithm divides the segmented signal in a **high-frequency sub-signal (HFSS)** and a **low-frequency sub-signal (LFSS)**. Then, the **instantaneous mean amplitude (IMA)** was calculated for the two sub-signals to ultimately obtain the fatigue index, which represents the difference between the IMA values of the LFSS and HFSS, respectively. The **high-frequency components** had been identified to be in the range of **80–350 Hz**. The **LFC** lay in the range of **25–79 Hz**. Then, the fast Fourier transform (FFT) was applied to these sub-signals to produce the LFSSf and HFSSf.

$$Fatigue\_Index = IMA_{LFSSfi} - IMA_{HFSSfi}$$

Below, the fatigue index of each person is presented. Iterations side by side for the 3 sessions performed by one person. We expected and can actually see that this index gets larger the more time the muscle is being used.



Moreover, in many cases the index gets higher by iteration, meaning that all 3 sessions were necessary to observe fatigue progression.

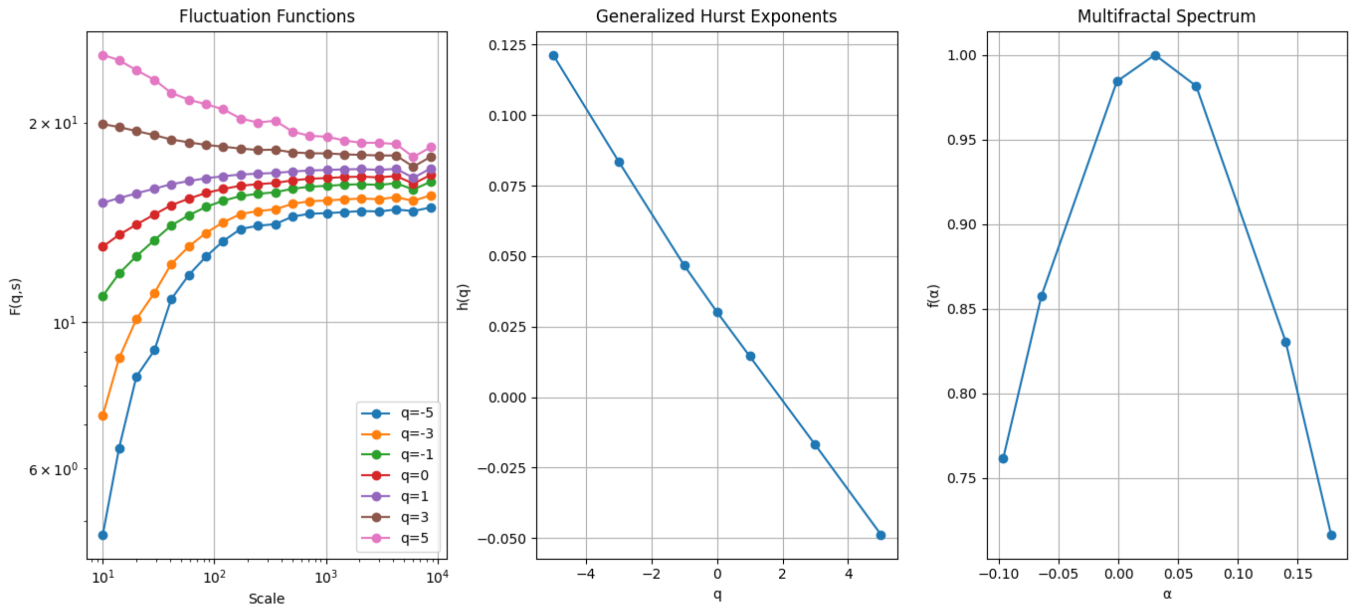


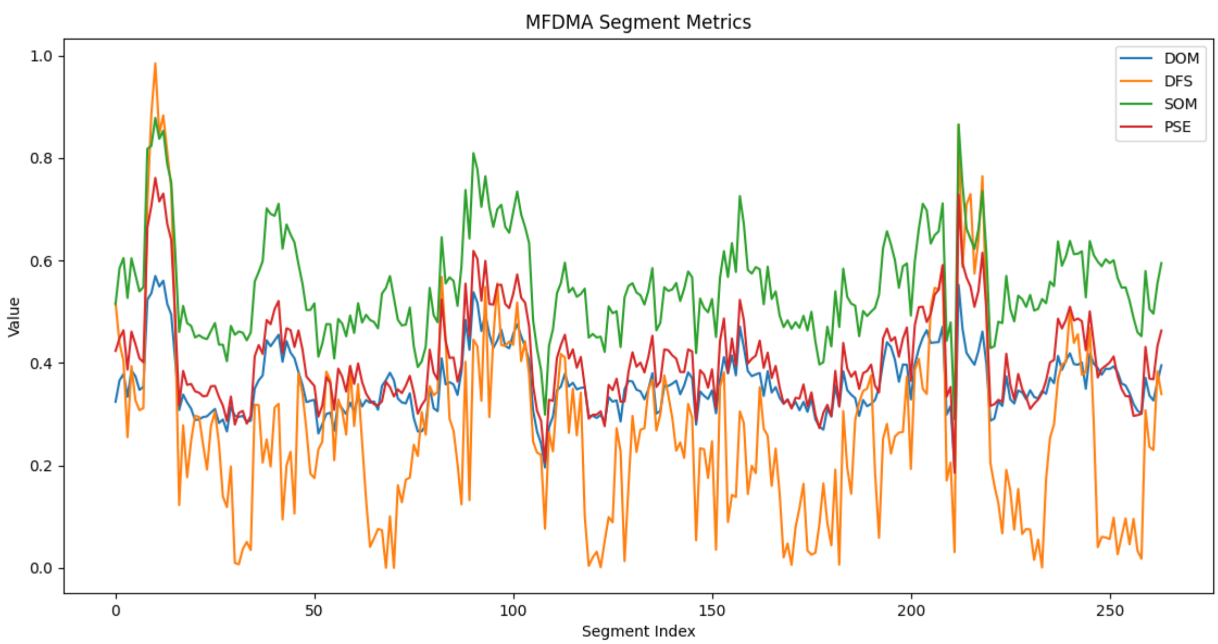
3. Multifractal Detrended Moving Average (MFDMA)

Another very promising work was done this year (https://doi.org/10.15632/jtam-pl/177321). This work is based on multifractal detrended moving average (MFDMA). According to the calculations that MFDMA can perform, the four multiple fractal characteristics of SOM, DOM, DFS and PSE widths of the multifractal spectra were wider during fatigue than when they were during non-fatigue.

- ✓ **SOM**: **Strength of Multifractality** (range of singularity strengths ($\alpha max - \alpha min$) in the multifractal spectrum.)
- ✓ **DOM**: **Degree of Multifractality** (range of Hurst exponents ($Hmax - Hmin$), which describe long-term correlations in the signal.)
- ✓ **DFS**: **Difference of Multifractal Spectrum** (height difference in the multifractal spectrum ($f(\alpha max) - f(\alpha min)$).)
- ✓ **PSE**: **Peak Singularity Exponent** (focuses on a specific point in the multifractal spectrum ($\alpha(q=-5)$), representing the dominant local scaling behavior.)

Below, there are two plots. In the first one there is the fluctuation functions based on the q order and the scale (window size), the Hurst exponents with the q values and the normalized multifractal spectrum with the singularity strength. Then in the second plot, the 4 metrics are presented calculated for each segment.



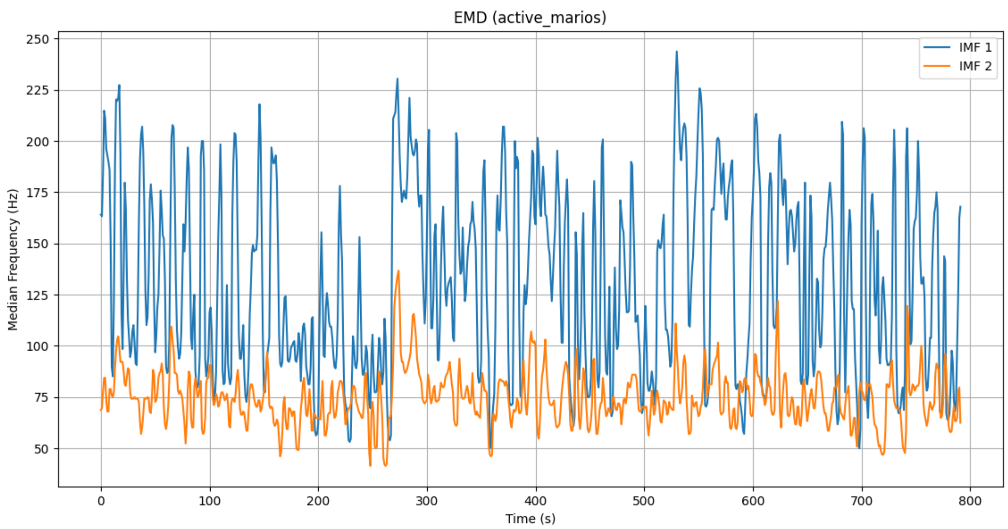


Trying to extract some meaningful results from these plots is not so easy, but improvements can be made, so we can test again the application of this study.

4. Empirical Mode Decomposition and Intrinsic Mode Functions

A useful nonstationary and nonlinear signal processing technique, known as empirical mode decomposition (EMD) combining Intrinsic Mode Functions (IMFs) (https://doi.org/10.3390/s19143108), was used. EMD adaptively decomposes the sEMG signal into IMFs, each representing oscillatory components corresponding to specific frequency bands without requiring predefined filters. Lower-order IMFs often capture high-frequency components, which are associated with muscle activation, while higher-order IMFs represent low-frequency trends, often linked to fatigue-related changes like signal amplitude reductions and spectral shifts.

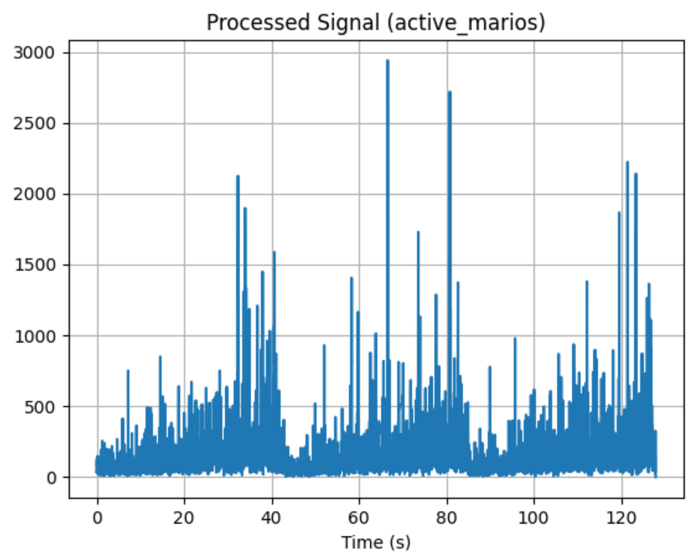
Below, are presented the IMF1 and IMF2 calculated from EMD, and plotted side by side for the 3 sessions of the participant.



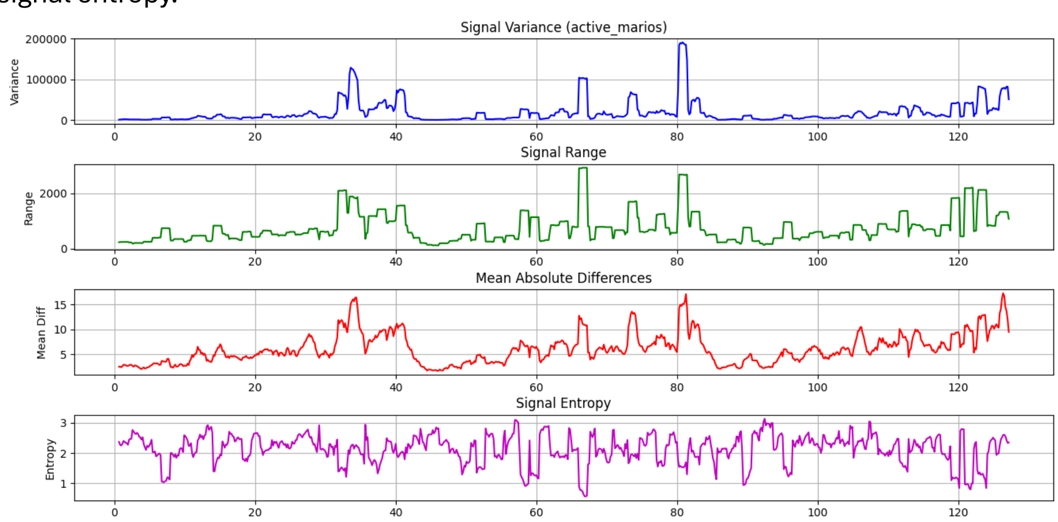
5. Scaled Fluctuations and Range, Variance, Mean Abs Differences and Entropy

Some very interesting metrics were derived while trying to perform the MultiFractal Detrended Moving Average. In order to understand this algorithm, we had to understand how **scaled fluctuations** work. A processed signal was calculated that represents a rescaled fluctuation profile obtained from detrending the input signal at multiple scales. It reflects how the signal fluctuates over varying segment lengths or resolutions, which can highlight features of the signal that may not be obvious in the raw data. Then, the signal is divided into windows of a certain size, with a sliding step. For each window, metrics such as **variance**, **range**, **mean absolute differences**, and **entropy** are computed.

Below it is presented the processed signal calculated as mentioned above. Side by side the 3 sessions performed by one participant.



Below, are presented the metrics discussed, variance, range, men absolute differences, signal entropy.



2. Regression Modeling for Fatigue Index Creation

1. **Objective**

To develop and monitor a new fatigue index by combining multiple fatigue-related metrics using regression techniques.

2. **Regression Model Development**

- The identified metrics will be used as inputs to train regression models.
- Experiments with various predictions of how fatigue trends over time during the task (e.g., linear increase, exponential decay, or other hypothetical fatigue curves).
- Design the model's output to estimate these expected fatigue trends.

3. **Training and Validation**

- Experiment with multiple regression techniques (e.g., linear regression, polynomial regression, or machine learning models).
- Evaluate the models based on their ability to predict trends that best align with fatigue progression.

4. **Outcome**

- Identify the best-performing regression approach.
- Demonstrate that the new fatigue index provides an accurate and reliable representation of fatigue progression, even in the absence of direct fatigue measurements.