Muscle Insight: Methods Analysis and Metrics of Value

# Introduction

Understanding and quantifying muscle fatigue provides valuable insights for applications ranging from sports science to medical diagnostics. This document focuses on the analysis methods and metrics associated with muscle fatigue, as identified in recent research studies. By exploring metrics highlighted in the literature, we aim to establish a foundation for evaluating their relevance and applicability in understanding muscle fatigue.

The document outlines key findings from the reviewed papers, discussing how these metrics may correlate with fatigue. Additionally, it provides an exploration of how these metrics can be leveraged for further research or practical applications in muscle insight analysis.

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# Papers

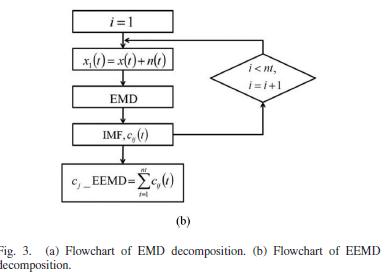
## Paper #1 (MNF, MDF, IMF, EEMD)

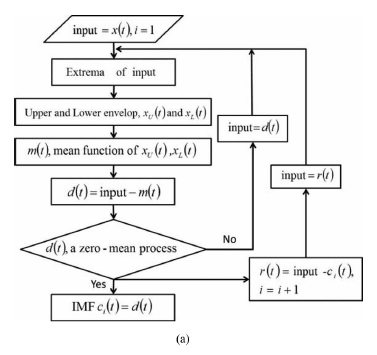
### *Summary*

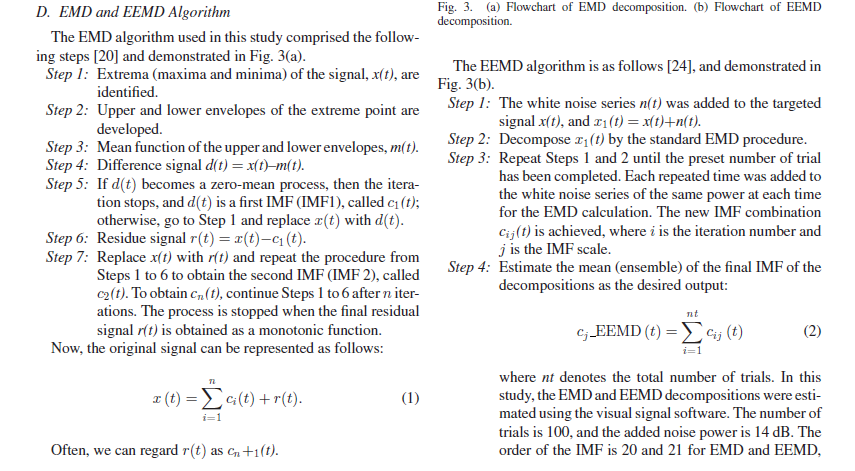
***The Progression of Muscle Fatigue During Exercise Estimation With the Aid of High-Frequency Component Parameters Derived From Ensemble Empirical Mode Decomposition***

It is well known that the power spectrum of the sEMG shifts to a lower frequency during a sustained muscle contraction. The spectral parameters, such as the mean frequency (MNF) and the median frequency (MF), are the manifestation of localized muscle fatigue.

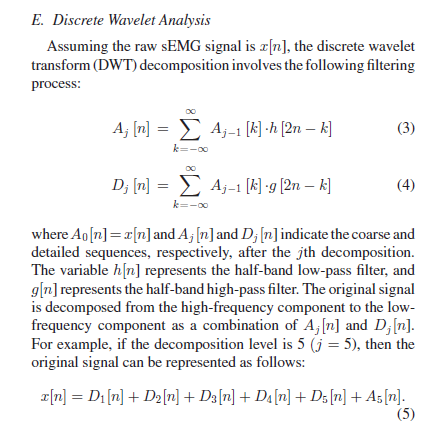
A useful nonstationary and nonlinear signal processing technique, known as empirical mode decomposition (EMD), has been proposed. With an iterative decomposition of signals, EMD separates the full signal into ordered elements with frequencies ranging from high to low in each intrinsic mode function (IMF) level. Results showed that HHT-derived (Hilbert-Huang Transform) spectral and linear regression parameters were consistent and more reliable than those obtained with the short-time Fourier transform and the wavelet transform.

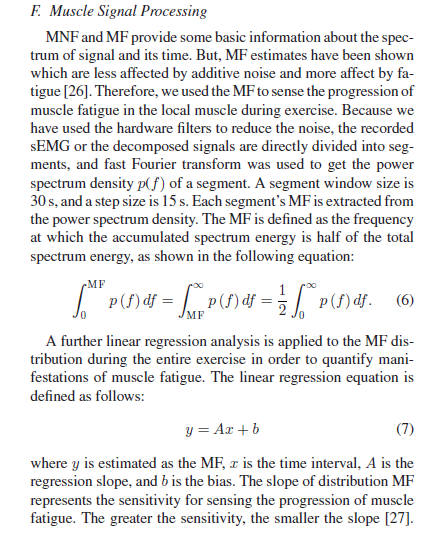
The procedure of the Ensemble EMD is to add statistically zero-mean noise into the signal with sufficient trials, and the ensemble IMF is estimated by the summation of the IMF from each trial of the same level. The goal of this study is not to quantify the myoelectric manifestation of muscle fatigue. Our goal is to find a more sensitive and stable method to sense the progression of muscle fatigue in the local muscle during exercise.

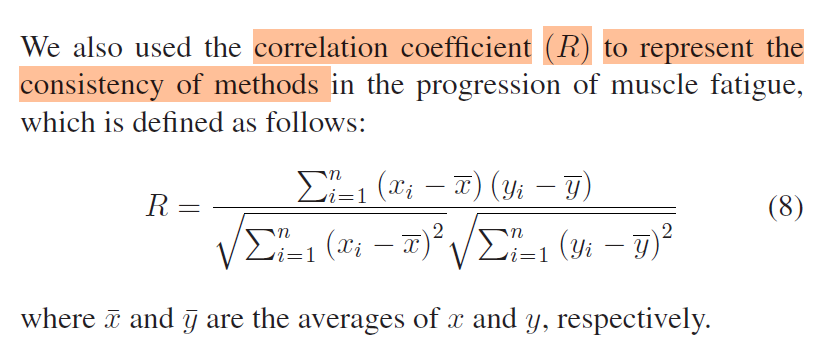




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### *Metrics Discussed*

1. Mean frequency (MNF) and the median frequency (MF) (Part F)
2. EMD , EEMD
3. DWT Discrete Wavelet Analysis

## Paper #2 (IMA\_lo – IMA\_hi)

### *Summary*

***Proposed Fatigue Index for the Objective Detection of Muscle Fatigue Using Surface Electromyography and a Double-Step Binary Classifier***

They suggested that the frequency spectrum of the EMG can be classified into three regions, namely,

* low-frequency components (LFC) (20–45 Hz),
* intermediate-frequency components (IFC) (46–80 Hz),
* high-frequency components (HFC) (81–350 Hz).

It is suggested that the power of the LFC increases, while that of the HFC decreases.

Fatigue occurs when the power of the LFC is equal to the power of the HFC (<https://ieeexplore.ieee.org/document/7591924/>).

The segmented EMG signal was filtered by two band-pass filters separately to produce two sub-signals, namely,

* a high-frequency sub-signal (HFSS) and
* a low-frequency sub-signal (LFSS).

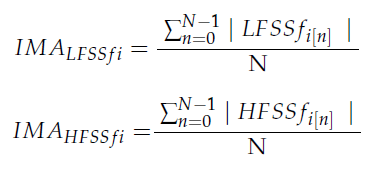
Then, the instantaneous mean amplitude (IMA) was calculated for the two sub-signals to ultimately obtain the fatigue index, which represents

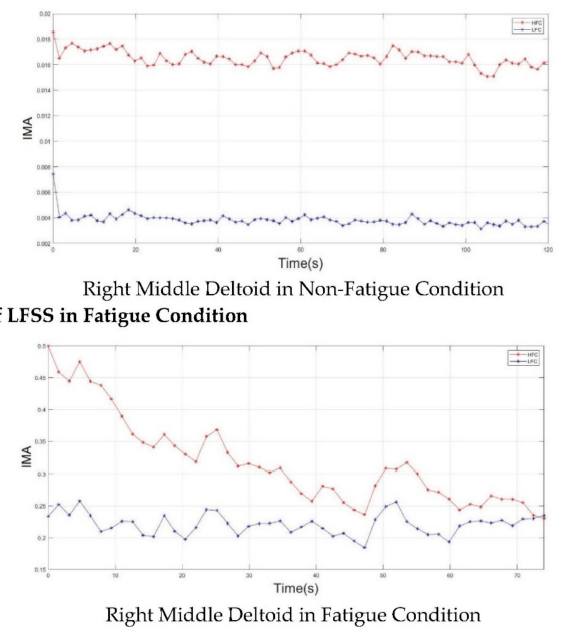
the difference between the IMA values of the LFSS and HFSS, respectively.

* 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.

An kai erxetai se antithesi me theoria einai afto pou ulopoieitai sto paper. Apofevgetai h xrhsh tou intermediate component.

Then, the fast Fourier transform (FFT) was applied to these sub-signals to produce the LFSSf and HFSSf.





For an accurate evaluation and in considering each sEMG signal as having segments of length N, the fatigue indices of the first and last three sEMG segments of all the subjects in fatigue condition were calculated. A fatigue index with a negative value was an indication of non-fatigue, while a zero or positive value was an indication of fatigue.

### *Metrics Discussed*

1. Fatigue Index = IMA\_lowComp – IMA\_highComp

## Paper #3 (Multifractal)

### *Summary*

***HIGH ACCURACY RECOGNITION OF MUSCLE FATIGUE BASED ON SEMG MULTIFRACTAL AND LSTM***

More research into changes in the local features of various levels of sEMG signals is necessary using the multifractal technology. A spectrum that depicts a subset and the appropriate fractal dimension is typically used to define multifractals. The major algorithms are:

* multifractal detrended fluctuation analysis (MFDFA)
* 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

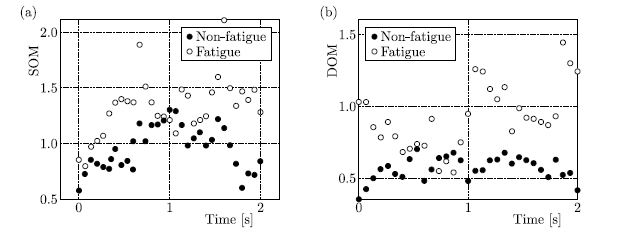
DOM: Degree of Multifractality

DFS: Difference of Multifractal Spectrum

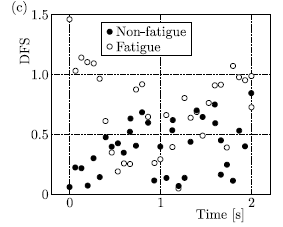
PSE: Peak Singularity Exponent

The multifractal spectra are symmetrical along the approximate axis in the non-fatigued condition, but with muscular fatigue, this symmetry tendency is greatly diminished.

The SOM, DOM and PSE features have clear feature distinctions between the non-fatigue and fatigue states, and the feature overlap rate of the two states is low,



whereas the DFS features have a greater overlap, and the distinction is less clear.



The difference between the aforementioned mean values of the properties of the myoelectric signals of 10 subjects under the fatigue and non-fatigue scenarios was observed using the t-test method in order to further determine whether the SOM, DOM, DFS and PSE extracted by the MFDMA algorithm have statistically significant differences under such scenarios.

According to the findings, the three characteristics (SOM, DOM and PSE) that were derived from the multiple fractal spectrum using the MFDMA method were statistically significant (P-value 0.01) in determining whether or not the muscles were exhausted.

Comparatively, the difference in DFS variability is relatively small. The findings could offer a fresh feature reference for deep learning and machine learning models that recognize muscle fatigue.

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### *Metrics Discussed*

1. multifractal spectrum f(a) and the singularity strength a(q)
2. Hurst exponents H(q) of the order q
3. SOM
4. DOM
5. DFS
6. PSE

### *Notes*

#### METRICS EXPLAINED

SOM – Strength of Multifractality

* SOM measures the range of singularity strengths (αmax−αmin​) in the multifractal spectrum.
* Larger amplitude fluctuations create a wider multifractal spectrum, increasing αmax−αmin​.
* In sEMG, as fatigue progresses, motor units fire irregularly, leading to more significant amplitude changes and a higher SOM value.

DOM - Degree of Multifractality

* DOM measures the range of Hurst exponents (Hmax−Hmin​), which describe long-term correlations in the signal.
* As muscle fatigue sets in, irregular motor unit recruitment causes the amplitude fluctuations to lose consistency, widening the range of Hurst exponents.
* H>0.5 suggests persistent trends (high amplitudes last longer), while H<0.5 suggests anti-persistent trends (amplitudes switch more often).

DFS - Difference of Multifractal Spectrum

* DFS measures the height difference in the multifractal spectrum (f(αmax)−f(αmin)).
* Larger asymmetries in amplitude changes (e.g., sharp spikes or drops) lead to more significant differences in f(α), increasing DFS.
* Fatigue often introduces these asymmetries due to chaotic motor unit behavior.

PSE - Peak Singularity Exponent

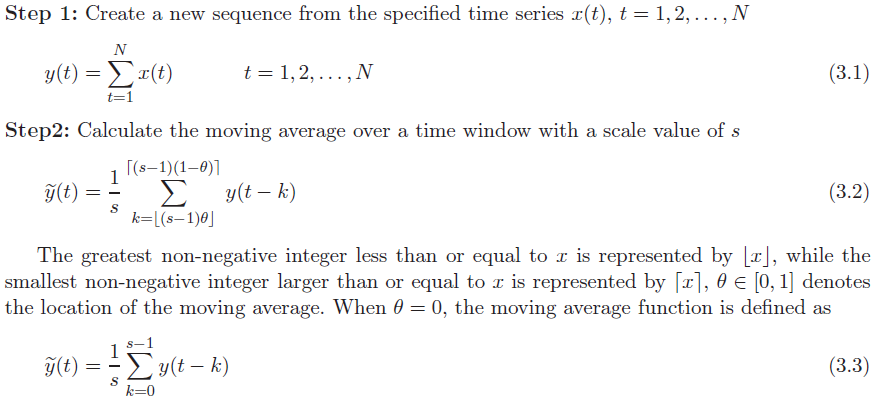
* PSE focuses on a specific point in the multifractal spectrum (α(q=−5)), representing the dominant local scaling behavior.
* The peak singularity captures the strength of the largest amplitude variations in the signal.
* Fatigue leads to more extreme amplitude changes, increasing PSE.

\*\*\* The Hurst exponent quantifies the tendency of a time series to either:

* Persist in its current trend (positive correlation in the signal),
* Revert to the mean (negative correlation), or
* Behave like a random process.

The value of H ranges between 0 and 1:

* H=0.5: The signal behaves like a random walk (no memory), (uncorrelated behavior).
* H>0.5: The signal shows persistent behavior, meaning high values are likely to be followed by high values, and low values by low values, (long-term positive correlations).
* H<0.5: The signal exhibits anti-persistent behavior, where high values are likely to be followed by low values, and vice versa, (long-term negative correlations).



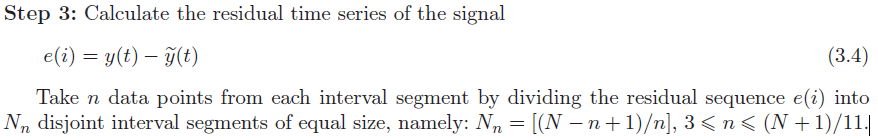
#### How to decide on θ?

The value of θ typically lies in the range [0,1].

* θ=0 would position the window at the start of the current sample, giving a right-aligned (causal) moving average.
* θ=1 would center the window, making it a symmetric (centered) moving average.
* Intermediate values of θ result in a window that is slightly shifted to the left or right.

Application to Muscle Fatigue:

To track muscle fatigue in real time and want the moving average to be updated immediately as new data comes in, a smaller θ closer to 0 might be appropriate. This would ensure that the output reflects the current and past muscle activity, without waiting for future data.

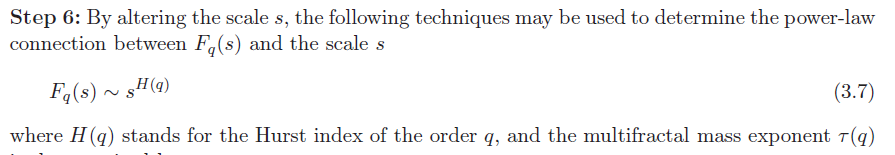


* The n data points in this context represent the window size,
* The formula Nn=[(N−n+1)/n] ensures that the segments do not overlap

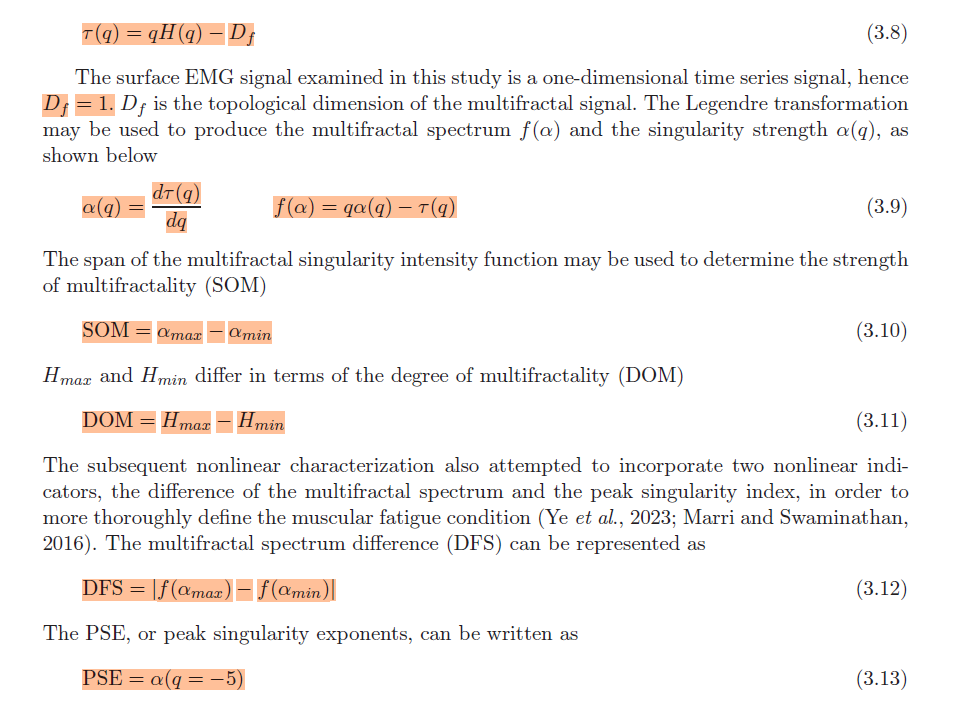
!!! This is MFDFA, not MFDMA !!! (Still you can have insights on the way this analysis works)

<https://pypi.org/project/MFDFA/>

<https://ar5iv.org/html/2104.10470v1>

Being able to calculate the Fq values and the H(q) values, for different window sizes and q values 

the next steps to be calculating are the following,



## Paper #4 (Time, Freq, Non Linear, MNF/ARV)

### *Summary*

**Estimation of Muscle Fatigue by Ratio of Mean Frequency to Average Rectified Value from Surface Electromyography**

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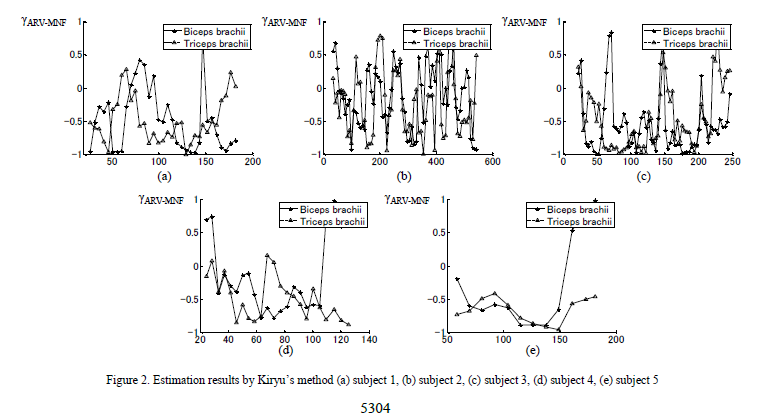
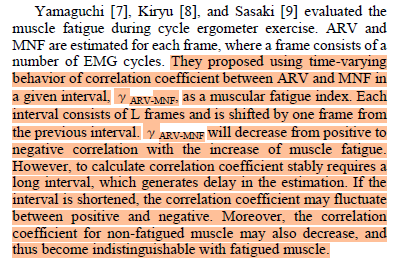
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Στο άρθρο στο οποίο έγινε η έρευνα, αναφέρονται τα εξής:



### *Metrics Discussed*

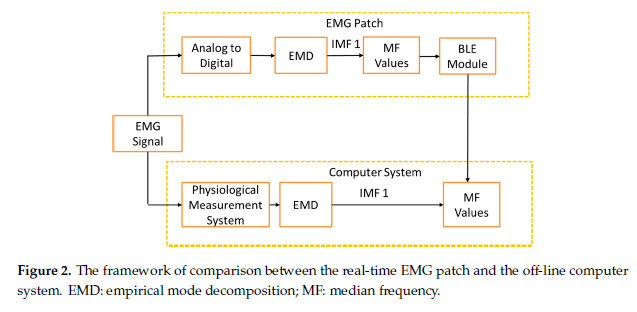
1. RMS, IEMG, ARV, ZeroCrossing
2. MPF, MNF, MDF, SMR, IMNF, IMFB
3. LZC, BandSpectralEntropy, WaveletEntropy
4. MNF/ARV

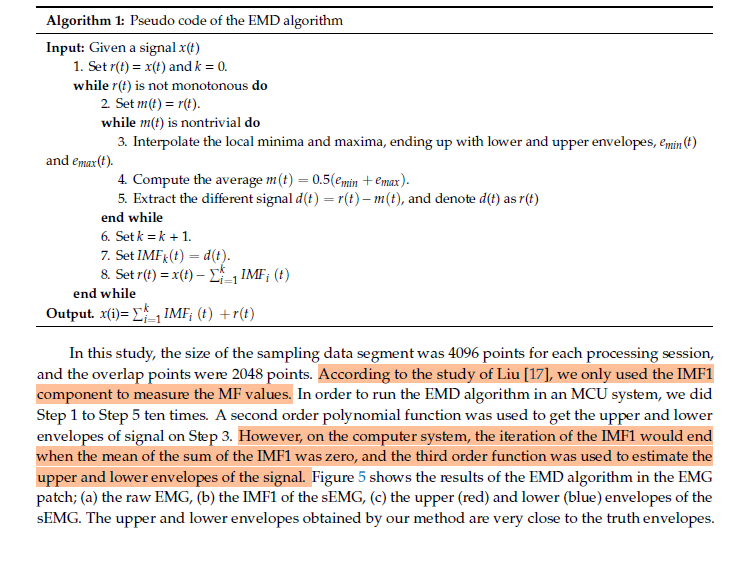
# Paper #5 (EMD, IMF, MedianFreq)

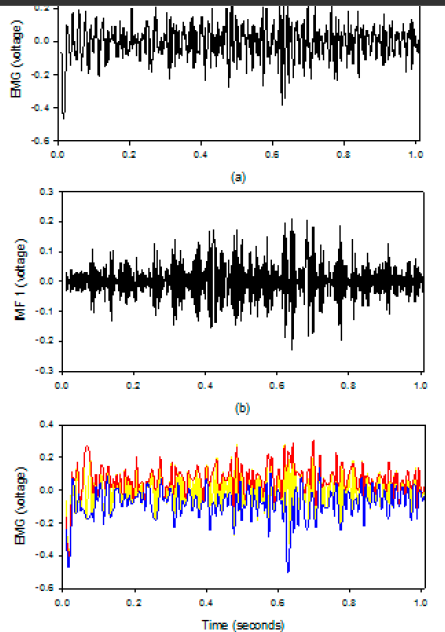
### *Summary*

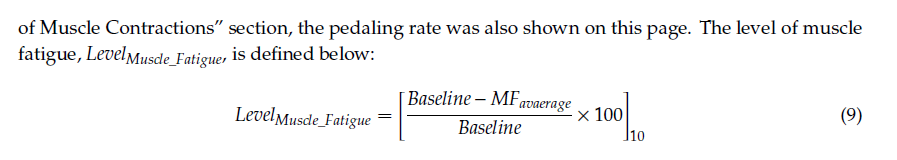
**An EMG Patch for the Real-Time Monitoring of Muscle-Fatigue Conditions During Exercise**

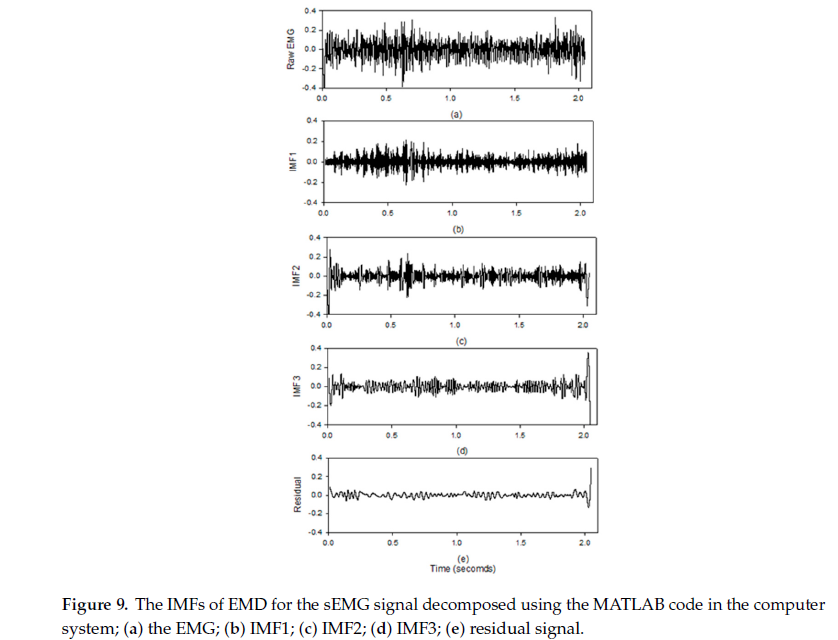
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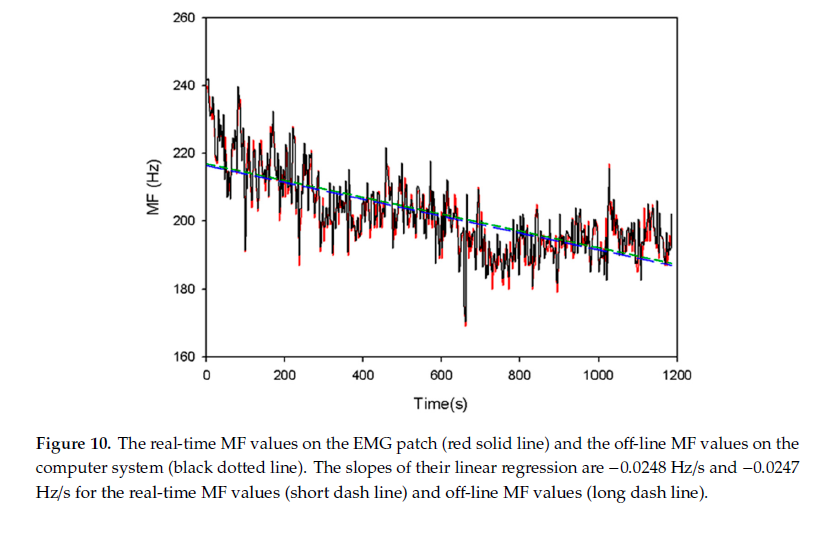












### *Metrics Discussed*

1. IMF 1, 2, .. , n
2. EMD
3. Median Freq (MF)

# Conclusions

We tried all the above metrics.

Related for sure:

1. Fatigue Index = IMA\_lowComp – IMA\_highComp
2. MNF/ARV
3. EMD (1st/2nd IMF)
4. Processed signal metrics
5. MFDMA ??

Not Good:

1. Correlation Coefficient of MNF with ARV
2. DWT Discrete Wavelet Analysis
3. EEMD ??
4. RMS, IEMG, ARV, ZeroCrossing
5. MPF, MNF, MDF, SMR, IMNF, IMFB
6. LZC, BandSpectralEntropy, WaveletEntropy