SPECTRAL ANALYSIS OF MUSCLE ACTIVITY - AN EXPERIMENTAL INVESTIGATION

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Abstract. *This article explores spectral analysis methods for muscle activity biosignals and presents experimental results. The research introduces a novel approach to this analysis, aiming to identify specific characteristics of muscle biosignals. Using the proposed method, muscle biosignals were recorded and processed during athletes' training sessions.*

Keywords: *biosignal, EMG, electromyography, parameter, frequency spectrum, segmentation, monitoring, signal processing, feature extraction, filtering, spectral analysis, feature vector.*

Introduction. Today, computer systems pervade every facet of our lives, including the field of medicine. The modernization of our country's medical sector necessitates such integration. Medical devices, diagnostic tools, and testing equipment increasingly depend on computer systems for their operation and control.

Biological signals, acquired through various means, undergo analysis to extract pivotal information. Standard techniques for signal analysis, such as filtering, digitization, processing, and storage, are applicable to many biological signals.

By processing electromyography (EMG) signals, specific outcomes become attainable. The digitization of received data is paramount due to its varied nature and transmission methods. For instance, data might be relayed through Bluetooth, Wi-Fi, or multiple ports, taking forms such as packets, text, graphics, or files.

Electromyography (EMG) measures the electrical activity produced by muscle fibers during contraction, resulting in electromyogram (EMG) signals. These signals are indicative of muscle tension [1,2]. EMG signals play a crucial role in numerous clinical and biomedical applications, from identifying muscular abnormalities to monitoring muscle activity.

EMG signals primarily serve to:

Pinpoint the timing of muscle activation.

Gauge the force muscles produce.

Examine muscle fatigue through the signal's frequency spectrum.

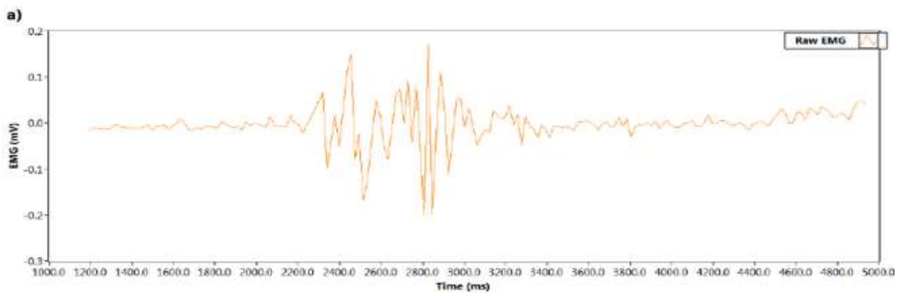
These uses underscore the multifaceted nature of EMG signals. The first focuses on the exact timing of muscle activation, vital for grasping motor control and coordination. The second quantifies muscle force, essential in biomechanics and rehabilitation. Lastly, frequency spectrum analysis of EMG signals assesses muscle fatigue, shedding light on muscle conditions during extended or intense activities.

EMG signals are valuable in diagnostic walking laboratories and are employed by trained clinicians for tasks such as biofeedback and ergonomic assessments. Their significance as biosignals spans biomechanics, motor management, neuromuscular physiology, movement disorders, postural control, and physiotherapy (Reaz et al., 2006). Clinical applications, such as gait analysis and coordination studies, necessitate the precise pinpointing of muscle activation timing and duration. Clinical specialists often favor visual inspection, granting a thorough signal evaluation. Additionally, algorithm speed becomes pivotal for specific applications, as does maintaining accuracy (Merlo et al., 2003).

Detecting voluntary muscle contractions is a crucial aspect of EMG processing. Its applications range from biomechanics to clinical diagnostics, rehabilitation tool development, and more. Through precise detection and analysis of these contractions via EMG, one can glean insights into human body mechanics, decipher movement patterns, muscle functions, and performance. Additionally, EMG-based diagnostics offer insights into muscle disorders, motor control deficits, and neuromuscular conditions. Data derived from EMG processing is paramount for creating efficient rehabilitation tools and interventions, enabling the formulation of tailored treatment plans and progress monitoring.

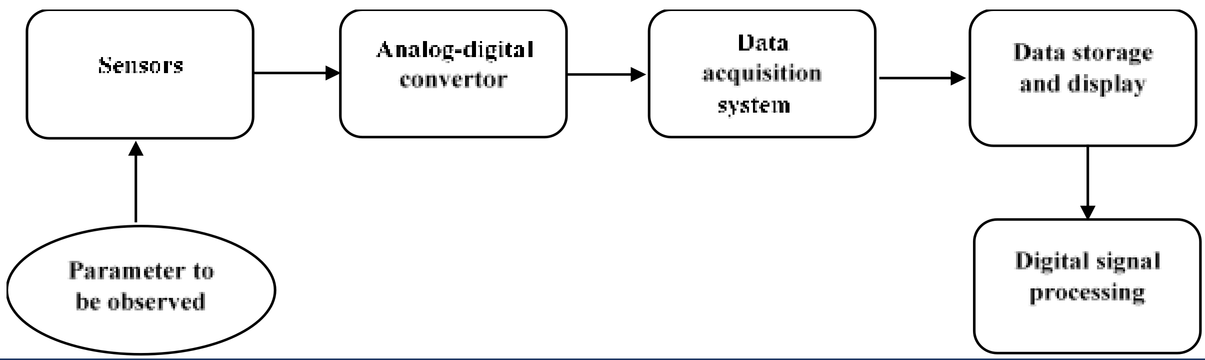
Methods and Algorithms for Processing Biosignals. The clinical assessment of a patient involves multiple stages, each with its distinct objective. Paraclinical techniques, such as electromyography (EMG), supplement this process by providing additional data that bolsters confidence in clinical hypotheses. Evaluating the efficacy of treatments and tracking disease progression are essential for pinpointing the specific type of pain or pathology. Throughout these stages, the primary goal of an EMG study remains to amass detailed information in the most efficient timeframe.

Figure 1. Appearance of the EMG signal (a signal recorded as a result of a single contraction and expansion of the biceps muscle).



Biosignals can be categorized based on multiple characteristics, including waveform and statistical structure. A primary distinction is between continuous and discrete signals. A continuous signal, represented as X(t), varies as a function of continuous time 't.' Typically, signals derived from biological events are continuous [3].

Figure 2. Block scheme of signal analysis.



Rohit Gupta and Ravinder Agarwal Method. The analysis of the electromyographic (EMG) signal adopts a block scheme comprising the following stages [4,5]:

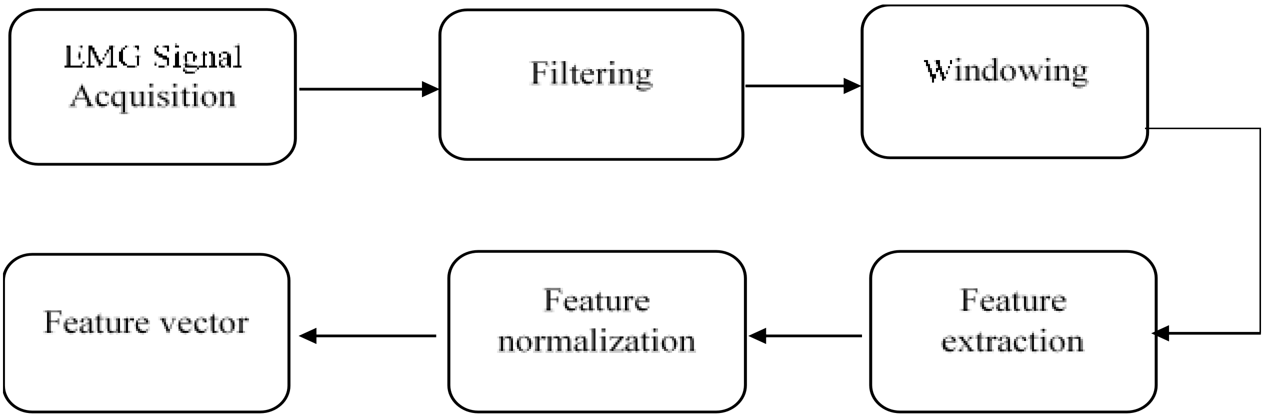


Figure 3. Block scheme of EMG analysis

EMG Signal Acquisition: Contemporary hardware is employed to record the EMG signal, capturing the muscles' electrical activity.

Filtering: The acquired EMG signal undergoes filtering to eliminate extraneous noise and artifacts, thereby improving the signal's quality.

Windowing: The refined signal is divided into smaller sections or 'windows,' making it conducive for more in-depth analysis and processing.

Feature Extraction: Specific characteristics of the EMG signal, such as amplitude, frequency, and time-domain traits, are extracted. These details furnish invaluable insights into the nature of muscle activity.

Feature Normalization: To guarantee uniformity and comparability across diverse signals or individuals, the extracted attributes are normalized. This step considers variations in signal amplitude and other potential factors.

Feature Vector Formation: By amalgamating the normalized features, a feature vector is formulated. This vector becomes the foundation for the subsequent phases of EMG signal analysis and interpretation.

Figure 4. Block scheme of the analysis of muscle activity biosignals.

The biosignals from muscle activity, once processed, underwent analytical scrutiny using the method proposed by Rohit Gupta and Ravinder Agarwal. This analysis leveraged a suite of machine learning algorithms, namely Decision Tree (DT), k-Nearest Neighbor (kNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA) [4,5,15]. The study by H. Jaffer and H. Ghaeb focused on devising a system for diagnosing neuromuscular disorders by analyzing muscle activity biosignals [6]." These adjustments aim to enhance clarity and maintain consistency in the structure of your sentences. If you have any further questions or need additional assistance, feel free to let me know!

The block scheme for electromyographic (EMG) signal analysis encompasses the following stages:

Recorded EMG: The electromyographic signal is captured through specialized sensors that detect the electrical activity of muscles.

Conventional Filtering: The acquired EMG signal undergoes specific filtering techniques, such as DC removal and band-limit filtering (typically in the 50-150 Hz range). These filtration methods aim to improve the quality and clarity of the biosignals for subsequent analysis.

Feature Extraction: Distinctive features are extracted from the biosignals to provide meaningful insights. Within the realm of EMG signal analysis, standard features encompass muscle fatigue (ascertained using the Fast Fourier Transform - FFT), signal power, and electrochemical delay characteristics.

The studies by the previously mentioned scientists were meticulously reviewed, culminating in the proposition of a dedicated algorithm for analyzing muscle activity biosignals, as depicted in [Fig 5].

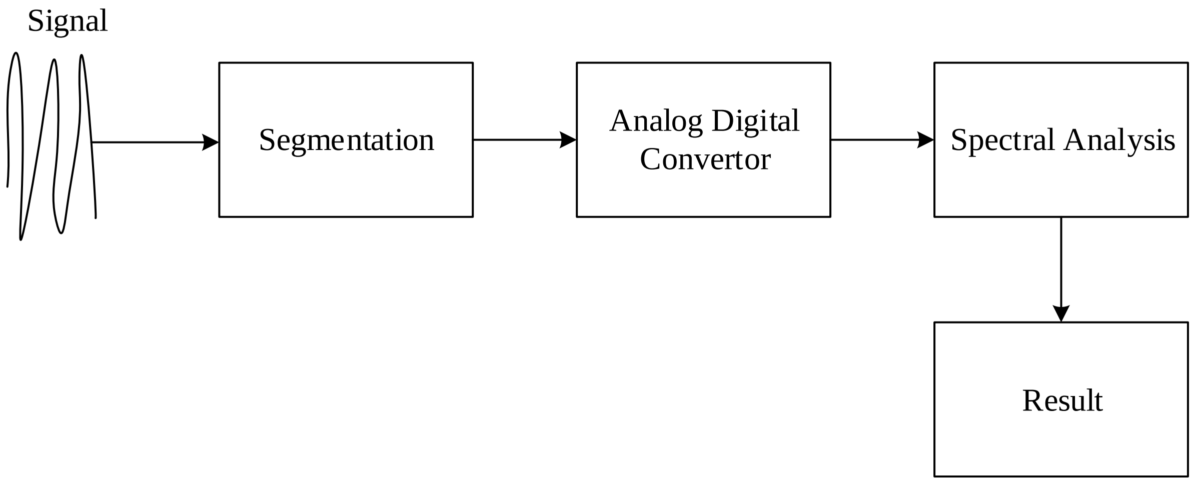


Figure 5. Block scheme of the spectral analysis of muscle activity biosignals.

The block scheme for the spectral analysis of muscle activity biosignals comprises the following stages:

Analog-to-Digital Conversion: The biosignals of muscle activity undergo conversion from analog to digital form using an analog-to-digital converter. For this purpose, the study employed the BTSFreeEMG sensor, equipped with both an analog-digital converter and a primary filter.

Segmentation: The biosignals are divided into smaller segments to facilitate subsequent analysis. Based on empirical research and analytical experiments, a segmentation length of 200ms and a sliding section of 100ms were identified as optimal parameters.

Spectral Analysis: At this juncture, the biosignals are assessed in the frequency domain. Techniques such as the Periodogram and Welch methods are utilized, yielding amplitude-frequency parameters that shed light on the signals' frequency content.

Result Presentation: The insights gleaned from the feature extraction process are visualized using graphs and tables, offering a holistic overview of the research findings.

To effectively execute and analyze our research objectives, setting up organized experiments was crucial. In this investigation, exercises were conducted with varying weights—specifically 1 kg, 3 kg, 5 kg, and 7 kg. Each weight was subjected to a testing duration spanning 5 weeks.

Welch's method provides an avenue to quantify the spectral power density. By employing this technique, one can discern and study fluctuations in the spectral power density of the acquired signal.

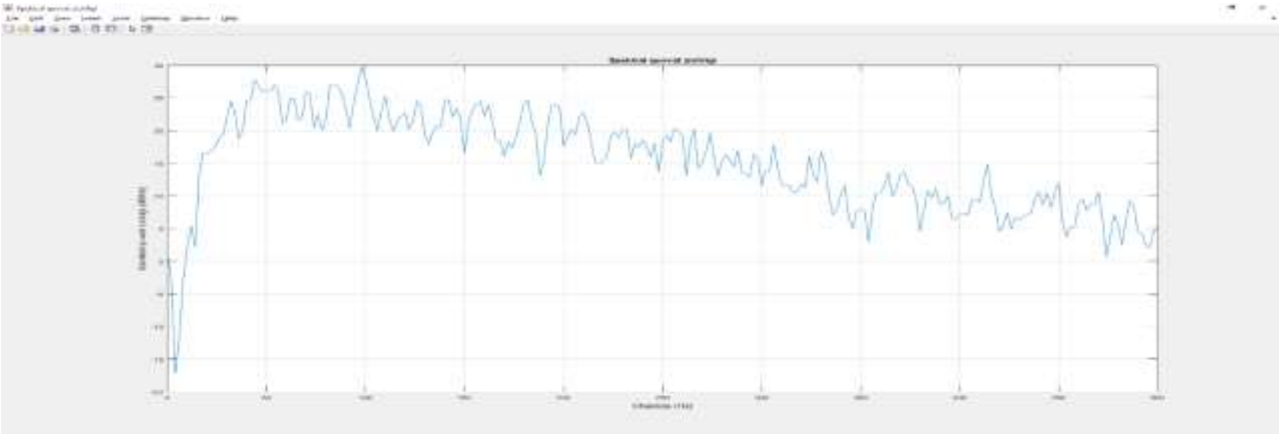
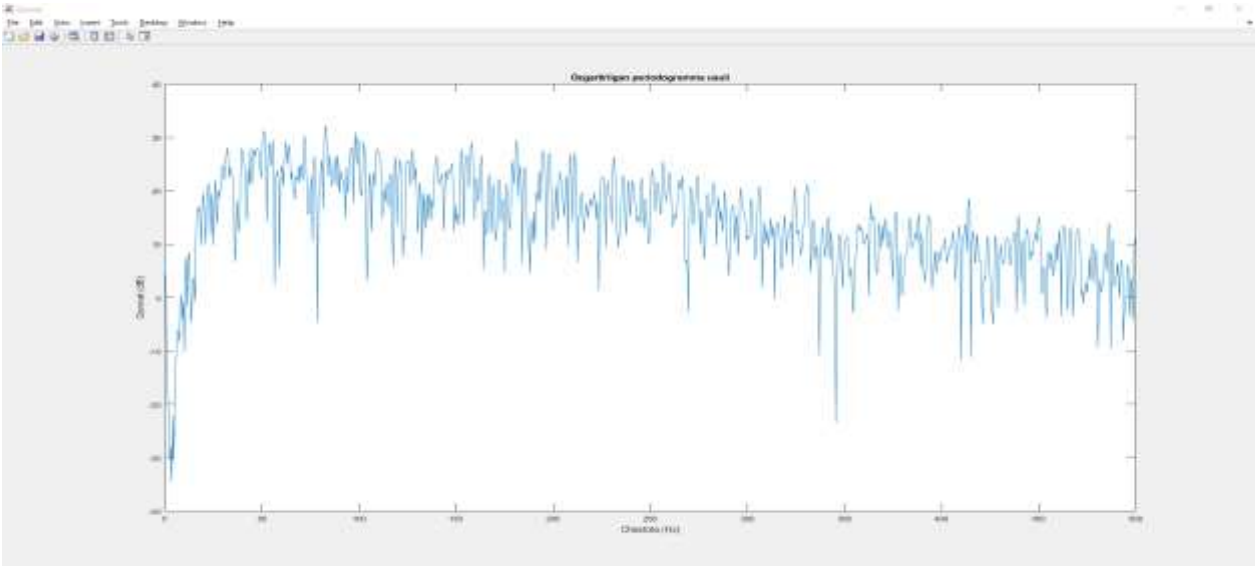


Figure 6. Power Spectrum Density.

A graph is instrumental in illustrating the Power Spectrum Density (PSD) in relation to its corresponding wavelength. Such a visual depiction elucidates the distribution of energy over varied wavelengths, granting a deeper understanding of the signal's spectral attributes.

Both the periodogram and Welch methods offer different modification capabilities. Specifically, the periodogram accommodates a range of alterations. Figure 7 showcases the energy output as interpreted by the fast Fourier transform via a periodogram.

Figure 7. Graphical representation of signal's power.



Results and discussion. The study's findings stem from the recorded and analyzed biosignals during the athlete's 35-day exercise regimen. This time frame facilitated the monitoring of shifts in the athlete's physiological and medical conditions and performance fluctuations. The results are depicted in Table 1, Figure 8, and Figure 9.

As illustrated in Table 2, the variations in power are graphically depicted in Figures 10 and 11.

Table1. Results Obtained By The Welch Method

	Week 1	*Week 2*	*Week 3*	*Week 4*	*Week 5*
1 kg	0,99	3,23	3,25	3,34	4,32
3 kg	3,64	4,56	4,59	6,06	6,07
5 kg	7,62	8,11	8,99	9,48	11,47
7 kg	7,61	9,5	9,5	9,68	11,68
9 kg	14,86	15,06	15,45	16,07	16,09

Table2. Results Obtained By The Periodogramm Method

	1 kg	*3 kg*	*5 kg*	*7 kg*	*9 kg*
Week 1	0,08	2,65	6,33	7,43	13,47
Week 2	1,06	3,09	7,33	8,83	14,15
Week 3	2,20	3,15	8,15	9,58	14,39
Week 4	2,23	4,23	8,66	10,67	15,11
Week 5	2,48	5,19	9,49	11,08	15,17

The periodogram method is adept at revealing power variations within muscle activity biosignals. For this study, weights of 1 kg, 3 kg, 5 kg, 7 kg, and 9 kg were employed. Across a span of 5 weeks, the power shifts in muscle activity biosignals were chronicled during exercises using the specified weights. The outcomes of the experiment were encouraging, demonstrating significant power alterations. Comprehensive data on these power transitions can be found in Table 2. The exercise recordings for each weight were undertaken over 5 days weekly.

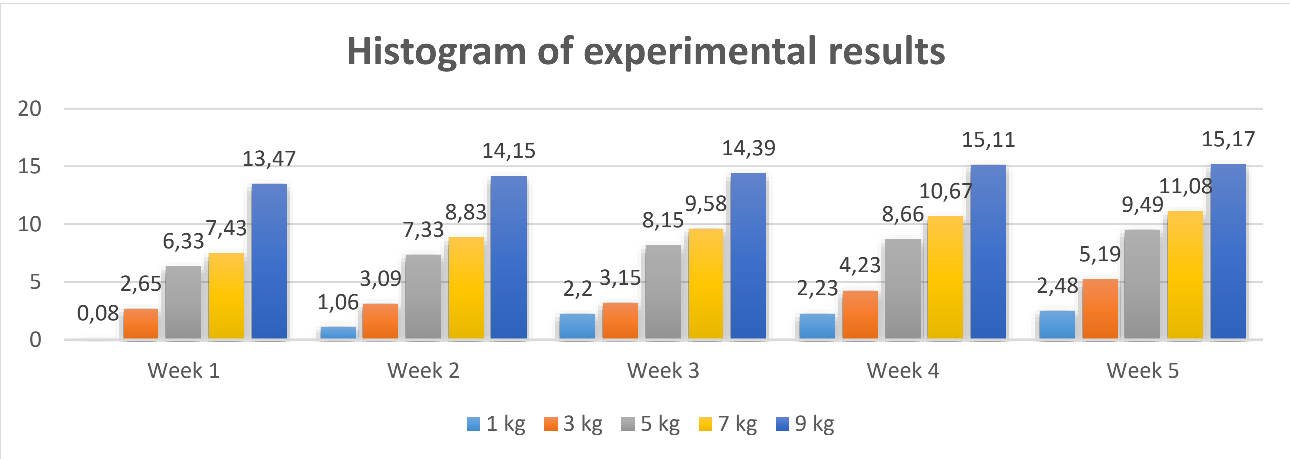


Figure 8. Results from the application of the Welch method in the experimental study.

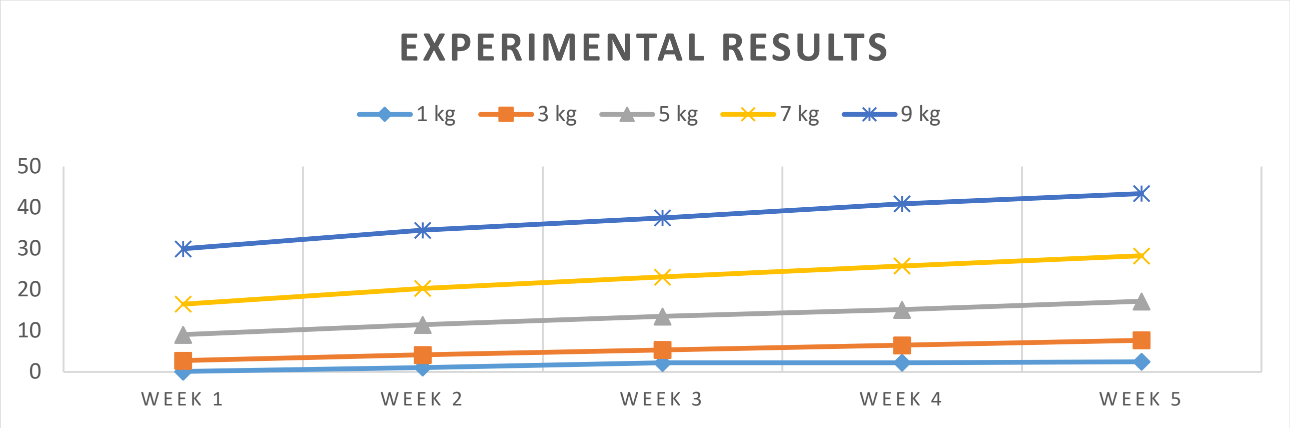


Figure 9. Graphical visualization illustrating the outcomes of the Welch method.

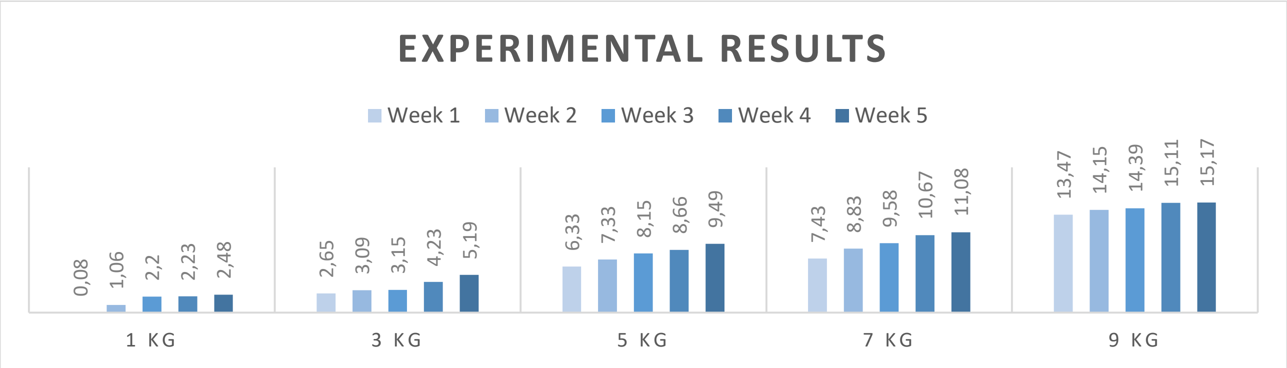


Figure 10. Graphical depiction of outcomes obtained using the Periodogram method in the experiment.

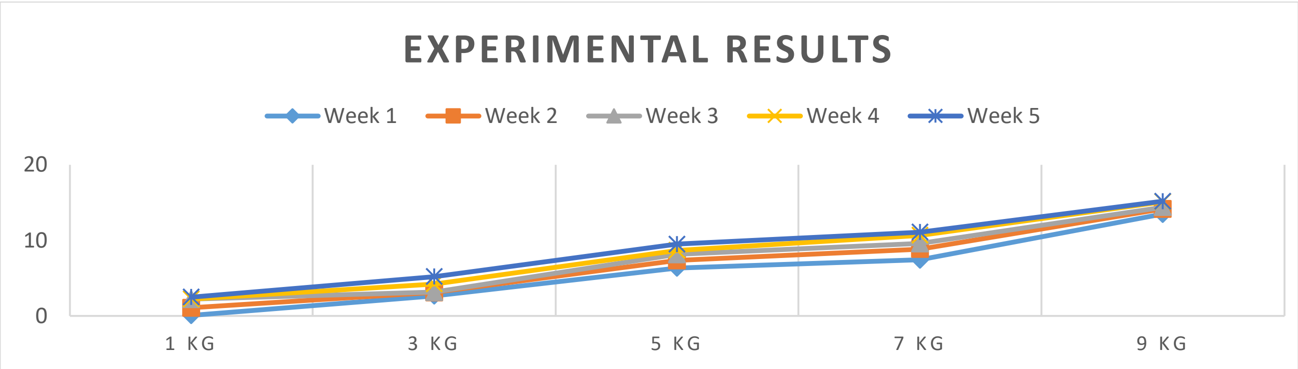


Figure 11. Visualization illustrating the analysis conducted using the Periodogram method.

Experiments were conducted to record power changes in the biosignals of human biceps brachii muscle activity using weights of 1 kg, 3 kg, 5 kg, 7 kg, and 9 kg. These findings hold considerable importance for tracking both the physical and biological states of athletes during training sessions. By employing the methods described, it is possible to efficiently capture and monitor analytical results, drawing from informative parameters within the biosignals of muscle activity.

The research underscores that tailored exercises designed to bolster the health and physical development of athletes can proactively address potential challenges they might encounter in their future endeavors.

Conclusion. This paper delves into the examination of algorithms employed in the medical domain for the analysis of biological signals. Our experiments underscore the profound influence of rehabilitative and analytical algorithms within the realm of sports. Notably, tailored exercises crafted for athletes or individuals undergoing rehabilitation can effectively track their physiological transitions and furnish them with consistent workout regimes.

The analysis extended to various facets of muscle activity biosignals, emphasizing the intrinsic features linked to them. Techniques for feature reduction and selection pinpointed the most salient and informative characteristics. Grounded in this scrutiny, algorithms were crafted to discern the prime features that showcase superior accuracy and efficacy in deciphering muscle activity biosignals.

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