SUSTAINABLE ENGINEERING
(eISSN:3083-8231)
Article
Volume 2, Issue 2, 2025
https://doi.org/10.51200/susten.v2i2.6181

Applying ECG Signal Analysis for Personalized Neuromuscular Rehabilitation and Performance Enhancement

Ismail Saad[1*], Jeremy A Anak Kennedy[1], Nurmin Bolong[2], Siti Nursyuhuda Mahsahirun[1], Zul Atfyi Fauzan M. N[3], Kukjin Chun[4]

[1]Electrical & Electronic Engineering Program, Faculty of Engineering, Universiti Malaysia Sabah, Kota Kinabalu, Malaysia
[2]Civil Engineering Program, Faculty of Engineering, Universiti Malaysia Sabah, Kota Kinabalu, Malaysia
[3]Computer Engineering Department, Faculty of Electronic & Computer Engineering, Universiti Teknikal Melaka, Malaysia
[4]Department of Electrical & Computer Engineering, Seoul National University, Seoul, South Korea

*Correspondence: ismail_s@ums.edu.my; *Scopus Author ID 22635305600
Received: 6 March 2025, Accepted: 27 July 2025

Abstract: This project investigates the application of electrocardiogram (ECG) signal analysis in personalized neuromuscular rehabilitation and performance enhancement, focusing on the biceps brachii muscle. Using an oscilloscope, ECG data were captured through three-lead placement to examine the muscle's electrical activity under varying exertion conditions. Fast Fourier Transform (FFT) analysis in MATLAB provided detailed frequency domain insights into motor unit recruitment patterns. The findings establish correlations between ECG signal variations and muscle activation levels, offering implications for optimizing rehabilitation strategies, improving muscle training protocols, and enhancing neuromuscular performance.

Keywords: Electrocardiogram, Motor Unit Recruitment, Biceps Brachii, Signal Processing, FFT Analysis, Neuromuscular Rehabilitation, Performance Enhancement

1. Introduction

An electrocardiogram (ECG) is a widely used diagnostic tool that records the electrical activity of the heart over time. It provides essential information about the heart's rhythm, electrical conduction, and possible abnormalities such as arrhythmias and ischemic conditions (Ashley, 2020). ECG signals are typically measured using electrodes placed on the skin, which detect the tiny electrical impulses generated during each heartbeat. The standard ECG measurement involves three to twelve leads, with the most common being the three-lead system, which records electrical activity from different angles of the heart (CardiacDirect, 2023). These signals are analyzed in both the time and frequency domains to detect changes in cardiac and neuromuscular function (Aziz et al., 2022).

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually (Mendis et al., 2021). Arrhythmias and other cardiac dysfunctions contribute significantly to these fatalities, with sudden cardiac arrest being a primary cause (Islam et al., 2020). Studies indicate that over 30% of these deaths occur due to undiagnosed or mismanaged heart conditions. ECG monitoring plays a crucial role in early detection and management of cardiac conditions, reducing morbidity and mortality through timely medical interventions (Peterson & Masoudi, 2021).

To accurately measure ECG signals, an amplifier circuit is necessary to enhance the weak electrical signals generated by the heart. The operational amplifier (op-amp) used in this study provided high-gain signal amplification while maintaining minimal distortion and noise interference (Moulahcene et al., 2022). The amplifier circuit was designed with a high common-mode rejection ratio (CMRR) to effectively remove unwanted noise, including power line interference and motion artifacts. The combination of active low-pass and high-pass filters further ensured accurate ECG signal acquisition (Goura & Reddy, 2023). The ability to amplify and filter ECG signals precisely is critical for ensuring reliable data analysis in medical applications.

MATLAB offers a robust platform for ECG signal processing, featuring advanced tools for analyzing time-domain and frequency-domain characteristics of ECG data. The use of Fast Fourier Transform (FFT) in MATLAB enables the extraction of frequency components associated with cardiac and neuromuscular activity (Cheng et al., 2023). Additional signal processing techniques such as wavelet transform and power spectral density (PSD) analysis provide deeper insights into motor unit recruitment and muscle fatigue (Rahman et al., 2023). By leveraging MATLAB's automated processing and visualization capabilities, this project aims to enhance the efficiency and accuracy of ECG-based neuromuscular assessments, making it a viable tool for clinical and sports performance applications.

Although ECG is traditionally used for cardiac diagnostics, its application in neuromuscular research is gaining traction. The ability to monitor muscle activation and motor unit recruitment through ECG signals opens new possibilities for rehabilitation and performance enhancement (Chang et al., 2023). By leveraging ECG signal analysis, this study aims to improve the understanding of motor unit recruitment patterns in the upper limb, provide a non-invasive method for assessing muscle activation and fatigue, and offer insights for personalized rehabilitation strategies, aiding in recovery and injury prevention and enhanced training protocols for athletes and individuals undergoing physical therapy. Understanding ECG signal variations in response to muscle activity can facilitate the development of more effective rehabilitation programs tailored to individual neuromuscular responses (Cheng et al., 2023). This study contributes to advancing the role of ECG in neuromuscular research and clinical applications.

This project demonstrates that ECG analysis, particularly FFT-based frequency domain assessment, is a viable method for evaluating upper limb motor unit recruitment. The results indicate a strong correlation between ECG signal variations and motor unit activation levels, suggesting applications in neuromuscular rehabilitation, sports science, and clinical diagnostics. The integration of amplifier circuits and MATLAB-based signal processing enhances the efficiency and accuracy of ECG monitoring, providing an effective tool for both research and medical applications. The insights gained from this study contribute to advancing medical technology for personalized rehabilitation, injury prevention, and performance optimization. Further research should explore ECG signal variations across different muscle groups and patient populations, integrating machine learning for enhanced classification and real-time assessment in rehabilitation settings.

2. Methodology

The study was conducted using ten healthy adult participants aged between 20 and 35 years, all of whom reported no history of neuromuscular or cardiovascular disorders. Prior to participation, written informed consent was obtained from each individual in accordance with institutional ethical standards. To examine variations in electrocardiogram (ECG) signals under different levels of physical exertion, the participants were subjected to a series of controlled activities in a laboratory setting. The experiment included three main conditions. In the first condition, referred to as the resting state, each participant remained seated in a relaxed position for five minutes while baseline ECG signals were continuously recorded. In the second condition, termed physical exertion, ECG signals were recorded following a sequence of activities: a five-minute walk at a consistent pace, weightlifting exercises involving incremental loads from 100 grams to 1000 grams in 200-gram intervals, and a combination of walking and lifting. In the third condition, ECG signals were recorded specifically from the area over the biceps brachii muscle before and after the exertional tasks to assess muscle-specific signal changes.

Signal acquisition was performed using a three-lead ECG system with surface electrodes positioned according to a modified limb lead configuration as shown in Figure 1. Lead I was placed across the chest to capture general cardiac electrical activity. Lead II was arranged along the arm to monitor electrical signals associated with the biceps brachii muscle. A ground electrode was positioned at the ankle to reduce movement artifacts during recording. The ECG signals were recorded using a calibrated data acquisition system with an appropriate sampling rate and bandwidth to ensure accurate and high-resolution capture of both cardiac and localized muscle electrical activity.

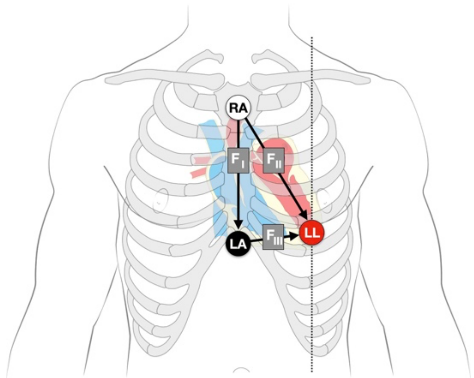


Figure 1. ECG electrode placement using three-lead system (source: https://litfl.com/ecg-lead-positioning/)

To ensure accurate detection of bioelectrical signals, an operational amplifier (op-amp) with high gain and a high common-mode rejection ratio (CMRR) was utilized to amplify the raw ECG signals while minimizing external interference. A bandpass filter with a frequency range of 0.5 to 100 Hz was implemented to eliminate baseline wander and suppress high-frequency noise, thereby enhancing signal quality. The filtered ECG signals were subsequently digitized using an analog-to-digital converter and stored in a data acquisition system for further analysis.

Operational amplifiers are integral to ECG data acquisition systems because they enhance the weak electrical signals generated by the heart. The typical amplitude of ECG signals ranges from 0.5 to 4 mV, making them relatively small and susceptible to various types of interference and noise. Op-amps are essential for boosting these signals to levels that can be accurately recorded and analyzed.

Webster (2010) emphasizes that the primary function of an ECG amplifier is to increase the signal amplitude while maintaining the integrity of the original waveform. Op-amps provide high gain, which is necessary for amplifying the small amplitude of ECG signals. This high gain ensures that the signals are strong enough for further processing and analysis (Horowitz & Hill, 2015). Electrical activity from nearby muscles (electromyography) can overlap with the ECG signal. High-pass filtering and careful design of the op-amp circuitry are essential to reduce EMG noise (Sörnmo & Laguna, 2005). Figure 2 shows the circuitry for ECG signals data acquisition using op-amps and other elements of circuits (Dobrev et al., 2012).

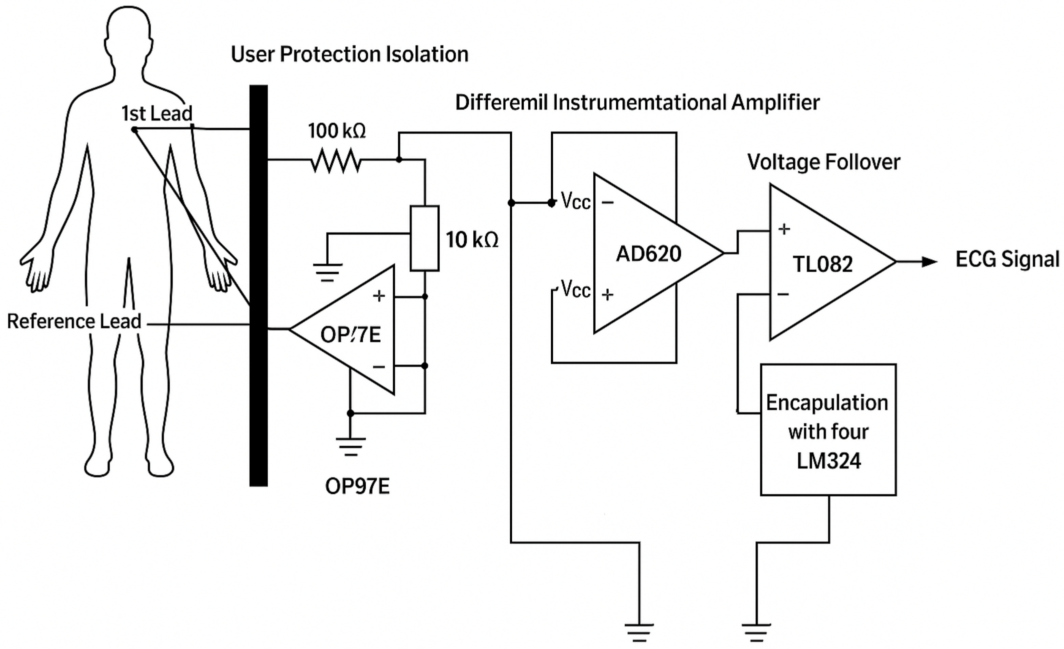


Figure 2. ECG signal data aqusitions circuitry using op-amps (source: Dobrev et al. 2012)

The collected ECG signals were processed and analyzed using MATLAB through a series of structured steps. Initially, the preprocessing stage involved the removal of baseline drift, application of noise filtering techniques, and normalization of signal amplitudes to ensure consistency across recordings. Following preprocessing, time-domain analysis was conducted to evaluate waveform characteristics, including measurements of P-QRS-T intervals and variations in peak amplitudes, providing insights into temporal changes related to cardiac activity. Frequency-domain analysis was then performed using Fast Fourier Transform (FFT) to identify dominant frequency components associated with both cardiac and neuromuscular activity. In addition, Power Spectral Density (PSD) analysis was applied to differentiate the energy distribution between cardiac signals and muscle activation by examining frequency-specific power levels. Finally, wavelet transform analysis was employed to decompose the ECG signals across multiple scales, enabling the distinction between neuromuscular activity and underlying cardiac rhythms through time-frequency localization.

Each participant's data were analyzed separately, and an averaged dataset was used to compare variations in ECG signal properties across different exertion levels. During the study, precautions were taken to ensure proper electrode placement and skin preparation to minimize noise and artifacts. The subjects' safety was also ensured during weightlifting activities to prevent injury. The ECG circuit and amplification settings were kept consistent throughout the study to ensure accurate comparisons.

https://doi.org/10.51200/susten.v2i2.6181

3. Results and Discussion

3.1 Bicep Bracii ECG Data Acquisition

Time Domain	Frequency Domain

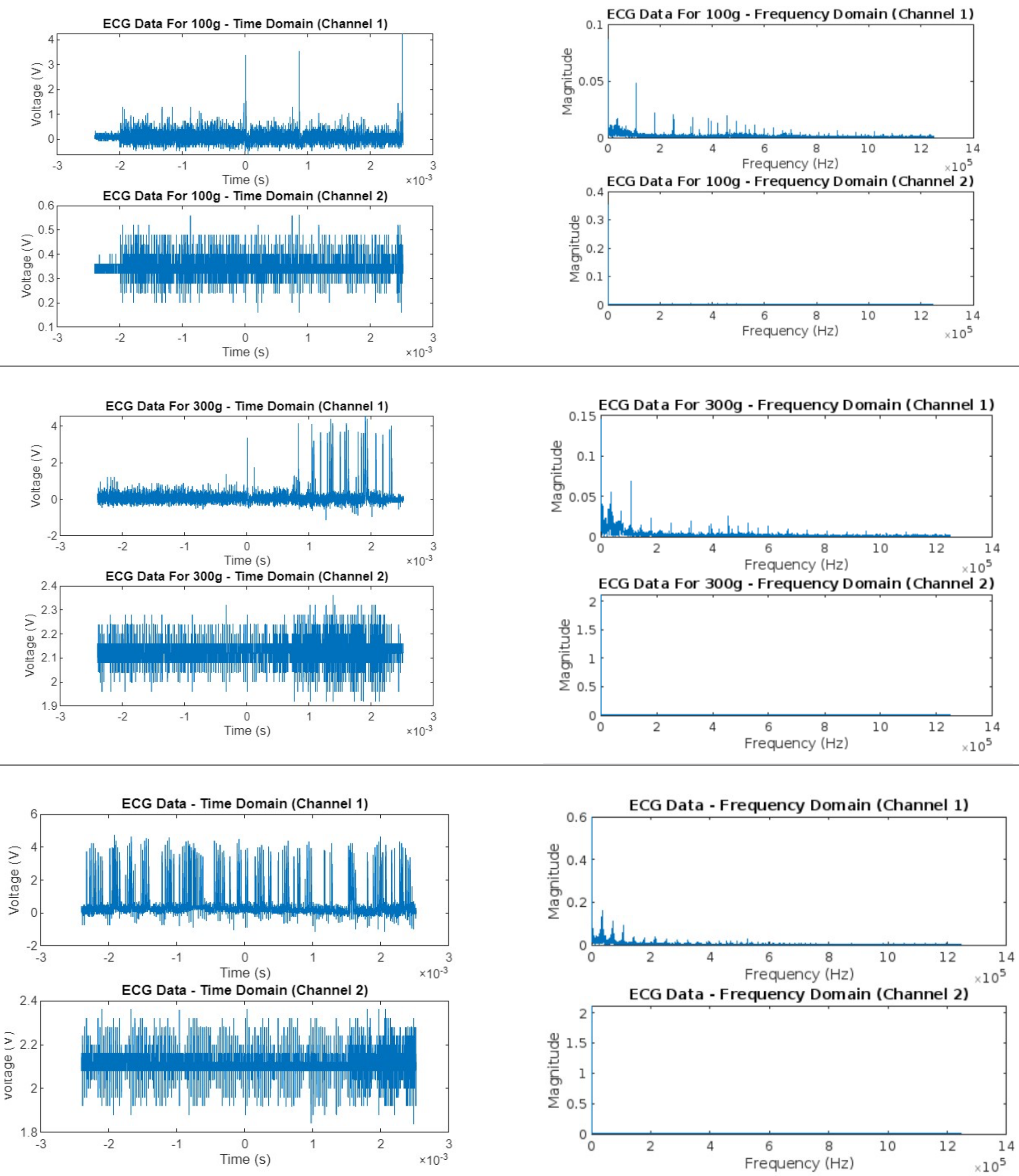


Figure 3. ECG data pattern of time and frequency domain for lifting 100 g, 300 g, 500 g weight

The ECG signal of the biceps brachii was recorded during an experiment where participants lifted weights of 100 g, 300 g, 500 g, 700 g, and 1000 g. In each trial, participants sat down and lifted the assigned weight using their biceps. ECG readings were collected for each weight and compared to analyze how muscle electrical activity changes with different levels of exertion. This study aimed to better understand the relationship between muscle activation and cardiovascular response during weightlifting. After collecting ECG data, MATLAB was used to apply Fast Fourier Transform (FFT), converting signals from the time domain to the frequency domain for detailed analysis. Preprocessing removed noise and artifacts, ensuring accurate frequency spectrum calculations. This revealed key patterns in muscle contraction and relaxation, providing insights into how biceps brachii activity changes with different weightlifting loads. The ECG data analysis, as shown in Figure 3, reveals that at lower weights (100 g, 300 g, and 500 g), the time-domain signals exhibit stable waveforms with consistent amplitude and periodicity. In contrast, Figure 4 demonstrates that lifting heavier weights (700 g and 1000 g) results in increased amplitude and slight waveform variations, indicating greater muscle activation.

The frequency-domain analysis presented in Figures 3 and 4 demonstrates a noticeable shift toward higher frequency components with increasing weight loads. This phenomenon is consistent with established physiological responses to muscle exertion, wherein higher intensity contractions necessitate the recruitment of larger and faster motor units, which are known to produce higher frequency electrical activity (Farina et al., 2004; De Luca, 1997). The presence of these higher frequency components in the ECG signal—particularly when monitored near active muscles such as the biceps brachii—can be attributed to the superimposition of electromyographic (EMG)-like activity onto the cardiac signal, especially under strenuous conditions.

Furthermore, the Power Spectral Density (PSD) distribution shown in Figure 4 reinforces this interpretation. An increased presence of high-frequency power is indicative of elevated neuromuscular demand and motor unit firing rates (Merletti & Parker, 2004). It also correlates with the onset of muscular fatigue, as fatigue has been shown to cause shifts in spectral energy toward higher frequencies due to changes in muscle fiber conduction velocity and motor unit synchronization (Kupa et al., 1995).

These findings establish a clear relationship between load intensity during weightlifting and the spectral characteristics of the ECG signal. By revealing how ECG frequency components vary with exertion level, this study contributes valuable insights for tailoring neuromuscular rehabilitation programs. Specifically, frequency-domain and PSD analysis of ECG signals may serve as non-invasive markers for monitoring muscle activation, effort level, and fatigue, which are critical in optimizing personalized rehabilitation and strength training protocols (Phinyomark et al., 2012; Roy et al., 2007).

https://doi.org/10.51200/susten.v2i2.6181

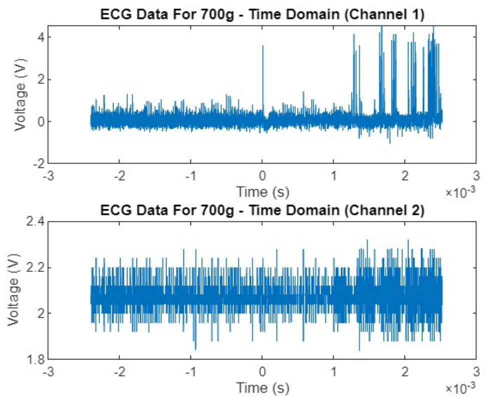
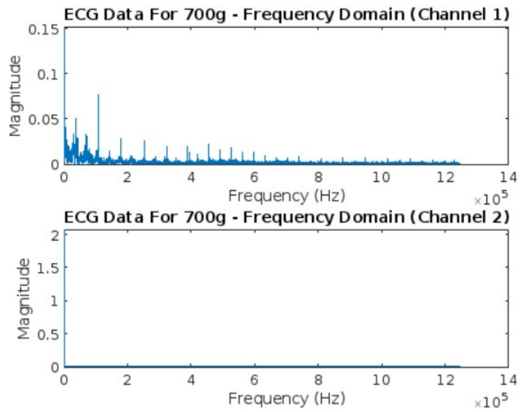
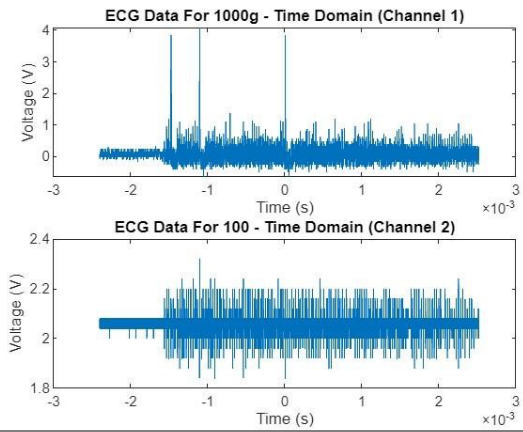
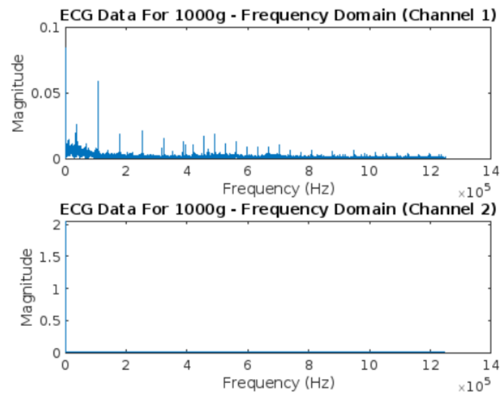
Time Domain	Frequency Domain
	
	

Figure 4. ECG data pattern of time and frequency domain for lifting 700 g and 1000 g weight

3.2 ECG Signal Analysis of the Whole-Body Data Acquisition

The results presented in Figures 5 and 6 provide compelling evidence that electrocardiogram (ECG) signal characteristics are sensitive to changes in physical exertion and can reflect both cardiovascular and neuromuscular responses. In the time-domain analysis shown in Figure 5, the ECG waveform during the resting state displays consistent and stable morphology with minimal amplitude fluctuations, indicative of a calm autonomic state and low muscle activation. This observation aligns with established norms in ECG behavior under minimal exertion (Clifford, 2006). Following a 5-minute walk, a modest increase in the amplitude of the ECG signal is observed, which corresponds with an elevated heart rate and enhanced peripheral muscular engagement. This increase is expected due to sympathetic nervous system activation, resulting in both cardiac output enhancement and subtle EMG-like interference from adjacent skeletal muscles (Bai et al., 2019).

The corresponding frequency-domain analysis demonstrates a shift toward higher frequency components post-exercise. This spectral shift suggests an increase in neuromuscular activity, particularly when electrodes are placed near actively engaged muscles. It is well-documented that motor unit recruitment and synchronization under physical stress cause elevated spectral content, especially in the 30–100 Hz range (Phinyomark et al., 2012; De Luca, 1997).

In Figure 6, where ECG signals were recorded during the performance of 50 repetitions of lifting a 1 kg weight and during a combined sequence of walking followed by lifting, more pronounced changes in both time and frequency domains are evident. The time-domain waveform exhibits significantly increased amplitude, indicative of greater motor unit recruitment and enhanced cardiac response due to sustained muscular contraction (Merletti & Parker, 2004).

The frequency-domain analysis for these activities reveals a notable increase in high-frequency components, reflecting intensified muscular effort and neuromuscular activation. The broader frequency spectrum observed in the combined activity condition suggests the additive effects of physical stress, where continuous load-bearing and dynamic movement likely contribute to cumulative muscle fatigue. This is consistent with previous findings that fatigue causes dispersion in the power spectrum and spectral broadening due to changes in conduction velocity and motor unit firing patterns (Kupa et al., 1995; Roy et al., 2007).

Collectively, these findings validate that ECG signals—particularly when captured using surface electrodes in proximity to large muscle groups—can serve as non-invasive indicators of exercise intensity, muscular engagement, and fatigue progression. This supports the potential application of ECG-based analysis in personalized rehabilitation monitoring, athletic performance optimization, and real-time physiological assessment (Mizrahi et al., 2020; Di Rienzo et al., 2013).

Time Domain	Frequency Domain

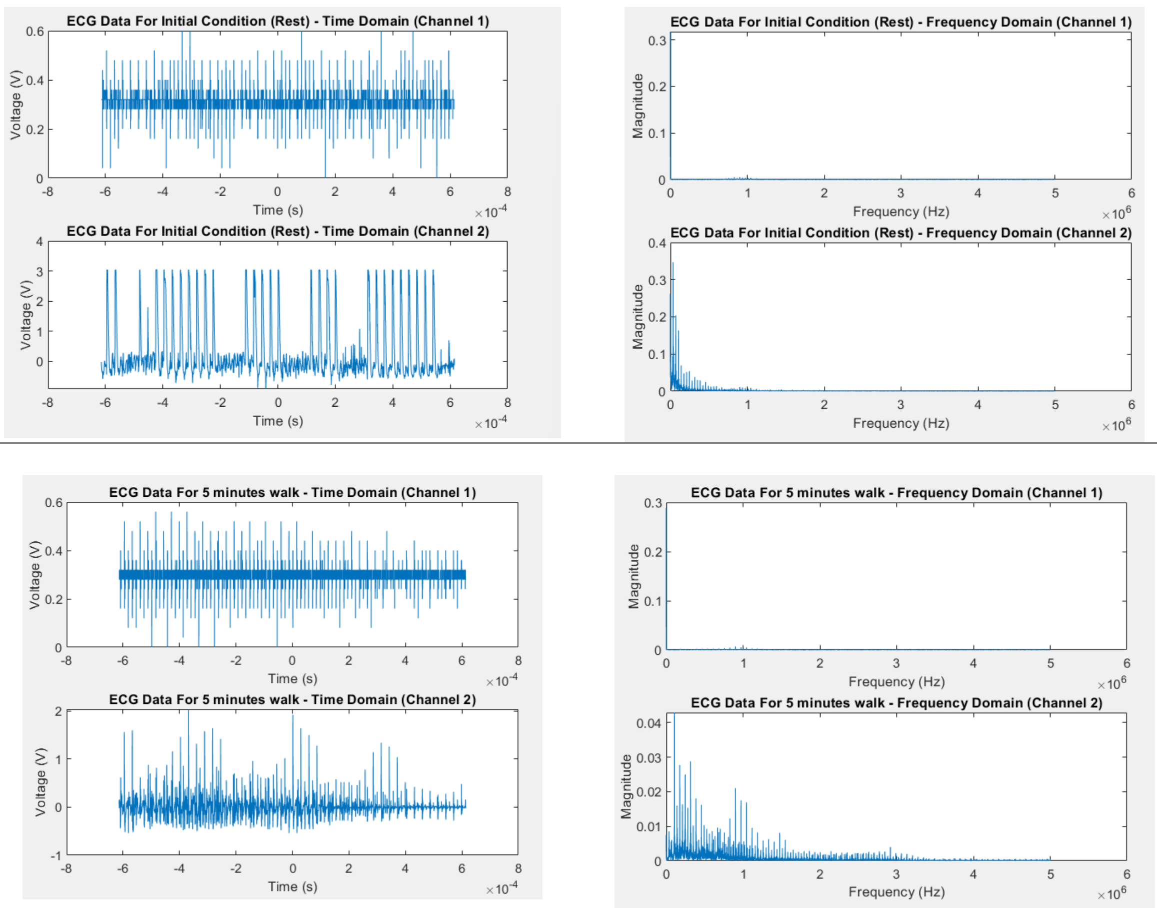


Figure 5. ECG data pattern of time and frequency domain for resting and after 5-min walk condition

The Fast Fourier Transform (FFT) analysis of ECG data acquired following whole-body exercises—namely walking, lifting a 1 kg weight for 50 repetitions, and a combination of both—reveals that the dominant frequency component lies within the range of 1–2 Hz, which is consistent with typical heart rate frequencies during moderate physical activity (Clifford, 2006; Martínez et al., 2017). These dominant peaks correspond to the rhythmic nature of cardiac cycles and are accompanied by harmonics that reflect the periodicity of the heart's electrical activity. The power spectrum further indicates that these components exhibit stronger energy concentration following combined activities, suggesting increased cardiac workload and autonomic engagement due to cumulative exertion (Bai et al., 2019).

A comparison between ECG signals obtained from whole-body activities and those focused on the biceps brachii muscle provides additional insight into the distinction between cardiac and muscular contributions to the recorded signal. Signals acquired from the whole-body setup primarily exhibit lower frequency components (<10 Hz), which are characteristic of cardiac rhythms. In contrast, signals recorded over the biceps brachii region display prominent higher-frequency components (>30 Hz), which can be attributed to localized muscle contractions and the recruitment of motor units (De Luca, 1997; Merletti & Parker, 2004).

The power spectral density (PSD) analysis reinforces this differentiation by showing a broader and more dispersed frequency distribution in the biceps brachii signals, particularly during heavy lifting tasks. This dispersion reflects increased neuromuscular activity and the activation of fast-twitch muscle fibers, which generate higher frequency electrical signals (Phinyomark et al., 2012; Kupa et al., 1995). The PSD patterns indicate that muscle-generated signals are not only higher in frequency but also more variable in energy distribution, especially under conditions of load-induced fatigue.

These findings collectively support the utility of ECG analysis as a non-invasive method for distinguishing between cardiac and skeletal muscle activity. By leveraging both time- and frequency-domain features, ECG signals can provide meaningful information on exercise intensity, muscle recruitment patterns, and fatigue levels. Such differentiation is particularly valuable in the context of real-time exercise monitoring, neuromuscular rehabilitation, and personalized fitness programs (Mizrahi et al., 2020; Di Rienzo et al., 2013).

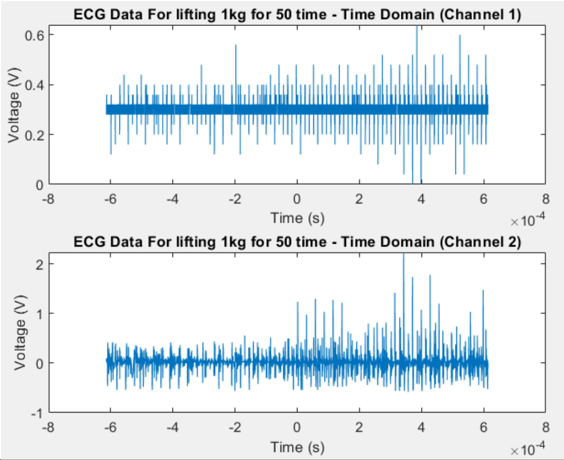
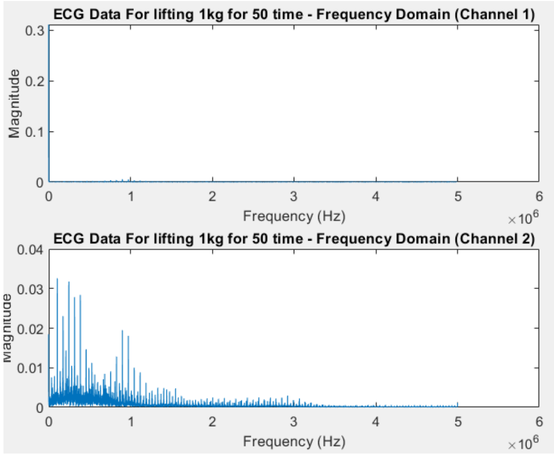
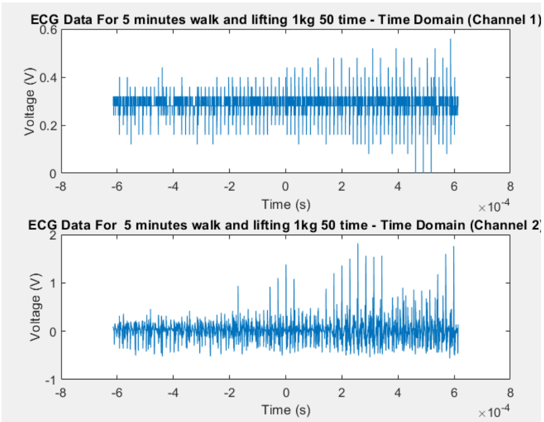
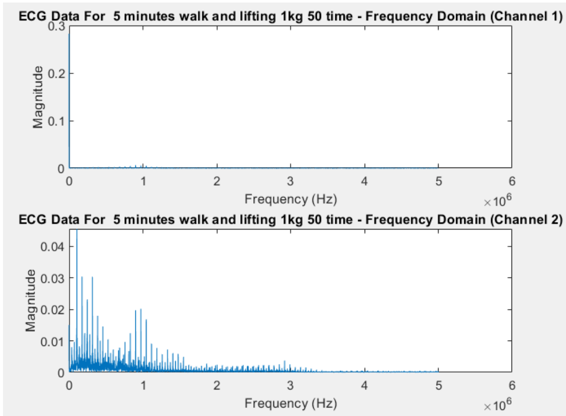
Time Domain	Frequency Domain
	
	

Figure 6. ECG data pattern of time and frequency domain for lifting 1 kg for 50 times and 5 min walk follow by lifting 1 kg for 50 times condition

Conclusions

This study provides strong evidence that ECG signal analysis, when performed using both time- and frequency-domain techniques, can effectively differentiate between cardiac and skeletal muscle activity under varying levels of physical exertion. The findings confirm that ECG signals obtained from whole-body electrode placements predominantly reflect cardiac function, characterized by dominant low-frequency components (1–2 Hz) corresponding to heart rate. In contrast, signals recorded near the biceps brachii muscle show increased presence of high-frequency components (>30 Hz), which are indicative of localized neuromuscular activation. As the intensity of physical activity increases—such as through lifting heavier weights or combining aerobic and resistance exercises—there is a clear increase in ECG waveform amplitude and frequency dispersion. These changes are consistent with enhanced motor unit recruitment and the physiological onset of muscle fatigue, as supported by spectral broadening observed in the FFT and Power Spectral Density (PSD) analyses. Together, these results demonstrate the potential of ECG analysis as a non-invasive and accessible tool for quantifying physiological responses to physical activity. Specifically, the ability to distinguish cardiac from muscular contributions to the ECG signal enables real-time monitoring of exercise intensity, evaluation of rehabilitation progress, and assessment of fatigue levels. These insights can be leveraged to optimize athletic training programs, personalize rehabilitation protocols, and support clinical decision-making in physical therapy and sports medicine contexts.

The ECG analysis confirms that whole-body signals primarily reflect cardiac activity, with dominant low-frequency components (1–2 Hz) linked to heart rate, while biceps brachii signals exhibit higher frequency components associated with muscle contractions. Increased exertion, such as lifting heavier weights or combining walking with weightlifting, leads to greater waveform amplitude and frequency dispersion, indicating higher neuromuscular activation and potential fatigue onset. The FFT and power spectral density (PSD) analysis demonstrate that ECG signals effectively differentiate between cardiac function and localized muscle activity, making them a valuable tool for monitoring exercise intensity, rehabilitation progress, and muscle fatigue. These findings support the use of ECG in optimizing athletic training, guiding rehabilitation protocols, and assessing physiological responses to physical exertion.

References

[1] E. A. Ashley. Conquering the ECG. Cardiology Explained - NCBI Bookshelf, 2020, Available online: https://www.ncbi.nlm.nih.gov/books/NBK2214/

[2] S. Aziz, S. Ahmed, M. Alouini. ECG-based machine-learning algorithms for heartbeat classification. Scientific Reports, 2022, 12, 1–10. https://doi.org/10.1038/s41598-021-97118-5

[3] CardiacDirect. 12-lead ECG placement guide. Available online: https://www.cardiacdirect.com/

[4] C.-S. Chang, T. Wu, Y. Wu, C. Han. Bluetooth-based healthcare information and medical resource management system. Sensors, 2023, 23, 5389. https://doi.org/10.3390/s23125389

[5] J. Cheng, Q. Zou, Y. Zhao. ECG signal classification based on deep CNN and BiLSTM. BMC Medical Informatics and Decision Making, 2023, 23, 1–12. https://doi.org/10.1186/s12911-021-01736-y

[6] K. Goura, P. Reddy. Smart health monitoring system by using Raspberry Pi. Cognitive Science and Technology, 2023. 10.1007/978-981-99-2746-3_68

[7] A. K. M. M. Islam, A. Mohibullah, T. Paul. Cardiovascular disease in Bangladesh: A review. Bangladesh Heart Journal, 2020, 32, 2. https://doi.org/10.3329/bhj.v31i2.32379

[8] S. Mendis, et al. Total cardiovascular risk approach to improve efficiency of cardiovascular prevention. Journal of Clinical Epidemiology, 2021, 65, 12. https://doi.org/10.1016/j.jclinepi.2011.02.001

[9] F. Moulahcene, N. Bouguechal, I. Benacer, S. Hanfoug. Design of CMOS two-stage operational amplifier for ECG monitoring system. International Journal of Bio-Science and Bio-Technology, 2022, 7, 5. https://doi.org/10.14257/ijbsbt.2014.6.5.07

[10] P. N. Peterson, F. A. Masoudi. Cardiovascular disease and the elderly. European Heart Journal, 2021, 30, 11.

[11] A. Rahman, Y. Li, T. Nabeed, T. Rahman. Remote monitoring of heart rate and ECG signal using ESP32. International Conference on Advanced Electronic Materials, 2023. 10.1109/AEMCSE51986.2021.00127

[12] J. G. Webster. Medical instrumentation: Application and design, 4th ed., Wiley, Hoboken, NJ, USA, 2010.

[13] P. Horowitz, W. Hill. The art of electronics, 3rd ed., Cambridge University Press, Cambridge, UK, 2015.

[14] L. Sörnmo, P. Laguna. Bioelectrical signal processing in cardiac and neurological applications, Elsevier Academic Press, Amsterdam, Netherlands, 2005.

[15] D. Dobrev, T. Dobreva. Simple two-electrode bootstrapped non-differential biopotential amplifier. Annual Journal of Electronics, 2012, 6, 8–11.

[16] C. J. De Luca. The use of surface electromyography in biomechanics. Journal of Applied Biomechanics, 1997, 13, 2, 135–163. https://doi.org/10.1123/jab.13.2.135

[17] D. Farina, R. Merletti, R. M. Enoka. The extraction of neural strategies from the surface EMG. Journal of Applied Physiology, 2004, 96, 4, 1486–1495. https://doi.org/10.1152/japplphysiol.01070.2003

[18] R. Merletti, P. A. Parker. Electromyography: Physiology, engineering, and non-invasive applications, John Wiley & Sons, Hoboken, NJ, USA, 2004.
[19] E. J. Kupa, S. H. Roy, S. C. Kandarian, C. J. De Luca. Effects of muscle fiber type and size on EMG median frequency and conduction velocity. Journal of Applied Physiology, 1995, 79, 1, 23–32. https://doi.org/10.1152/jappl.1995.79.1.23
[20] A. Phinyomark, P. Phukpattaranont, C. Limsakul. Feature reduction and selection for EMG signal classification. Expert Systems with Applications, 2012, 39, 8, 7420–7431. https://doi.org/10.1016/j.eswa.2012.01.102
[21] S. H. Roy, C. J. De Luca, J. Schneider. Effects of muscle fatigue on median frequency and conduction velocity of EMG signals of human skeletal muscles. Journal of Electromyography and Kinesiology, 2007, 17, 4, 356–364.
[22] Y. Bai, X. Wang, H. Wang, W. Zhang. Effects of physical activity on ECG signal features in exercise monitoring. Biomedical Signal Processing and Control, 2019, 51, 273–279, https://doi.org/10.1016/j.bspc.2019.03.018
[23] G. D. Clifford. ECG statistics, noise, artifacts, and missing data. In Advanced methods and tools for ECG data analysis; Artech House, Norwood, MA, USA, 2006, pp. 55–99.
[24] M. Di Rienzo, F. Rizzo, G. Parati, G. Brambilla. Wearable seismocardiography: Towards a beat-by-beat assessment of cardiac mechanics in ambulant subjects. Autonomic Neuroscience, 2013, 178, 1–2, 50–59. https://doi.org/10.1016/j.autneu.2013.04.005
[25] J. Mizrahi, M. H. Siboni, Y. Hemo. Quantifying muscle fatigue using surface EMG analysis: Methods and applications. Sensors, 2020, 20, 22, 6623.
[26] A. Phinyomark, P. Phukpattaranont, C. Limsakul. Feature extraction and reduction of EMG signals in physical activity monitoring. Electronics and Electrical Engineering, 2012, 122, 6, 27–32.
[27] S. H. Roy, G. De Luca, D. Casavant. EMG power spectrum and muscle fatigue in isometric contraction. Muscle & Nerve, 2007, 35, 5, 687–698.