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Development of a Low-Cost EMG Monitoring and Signal Processing System for Drill Operators

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Abstract*— This study presents the development of a low-cost system for real-time monitoring and processing of electromyographic (EMG) signals to study the impact of mechanical vibrations on drill operators, which are known to lead to musculoskeletal disorders and reduced work efficiency. The proposed system comprises an EMG acquisition unit, a vibration generator, and signal processing algorithms to ensure noise reduction and robust data analysis. Signal processing techniques, including notch filtering and Empirical Mode Decomposition (EMD), were employed to ensure high-fidelity signal analysis. Preliminary testing in controlled environments demonstrated the system's ability to detect the presence of vibrations when using a drill, not the vibration generator, which suggests that muscle activation arises not merely from exposure to vibrations but from the body's efforts to compensate for such stimuli. Observed results indicate the system can detect real-time vibration exposure and its intensity. A third-party Motor Unit Action Potential (MUAP) estimation algorithm was implemented, which could allow the preventive detection of musculoskeletal disorders. The proposed system holds potential for broader ergonomics, rehabilitation, and sports science applications. By offering a portable, cost-effective solution, it addresses a critical gap in real-time monitoring technologies. Future directions include more rigorous testing in real-world settings, exploring the effects of different vibration frequencies, intensities, and directions with a vibration platform, and exploring the use of Artificial Neural Networks (ANN) to help draw actionable conclusions from patterns in MUAP estimation.

Keywords: Electromyography, Mechanical Vibrations, Signal Processing, Real-Time Monitoring, Empirical Mode Decomposition, Signal to Noise Ratio, MUAP estimation

I. INTRODUCTION

Drilling operations are essential across various industries, often requiring workers to operate heavy machinery in demanding environments. These challenging tasks frequently expose operators to mechanical vibrations, which pose significant health risks, including musculoskeletal disorders and vascular issues, that can severely impact a worker's quality of life and long-term health [1]. These risks are particularly pronounced in mining, construction, and manufacturing industries, where workers frequently operate heavy vibrating tools and machinery for extended periods without adequate protective measures [2].

Prolonged exposure to such conditions often results in adverse outcomes, such as Raynaud's phenomenon, sensorineural impairment in the fingers, carpal tunnel syndrome, and osteoarthritis [3]. Over time, workers may experience reduced grip strength, chronic pain, and even permanent nerve and blood vessel damage. In severe cases, these conditions can render individuals unable to perform basic tasks, both professionally and personally [4]. This highlights the urgency of implementing effective monitoring and mitigation strategies to prevent long-term health consequences.

Despite the known risks, most research on electromyography (EMG) monitoring during vibration exposure has been focused on rehabilitation or performance enhancement, commonly referred to as rehabilitation vibration therapy, as it has been proven to cause acute increases in muscle activation [5]. Monitoring these activation levels using EMG could help prevent these adverse outcomes [6][7]. Still, research exploring the effects of vibrations as a workplace hazard remains notably scarce.

Furthermore, solutions for monitoring and mitigating these risks, especially in resource-constrained environments, are limited. The number of vibration syndrome cases reported is small, partly because physicians commonly fail to diagnose the syndrome, and workers tend not to report it. This underreporting indicates a reactive approach to diagnosis, where issues are addressed only after significant harm has occurred [8]. This underscores the critical need for innovative, preventive strategies to identify risks early and help safeguard workers in vibration-prone industries. A proactive approach is necessary to bridge the gap between research and practical workplace safety measures.

To address this gap, this research aims to develop a low-cost, real-time monitoring system based on EMG signal acquisition and processing. By prioritizing affordability and accessibility, the proposed system offers a practical means of detecting the effects of mechanical vibrations on workers, making it especially valuable for smaller operations where high-cost solutions are not feasible. Doing so contributes not only to a deeper understanding of vibration exposure, as research regarding EMG activity in these conditions is scarce, but also to developing effective preventive strategies that can reduce workplace injuries. Its real-time monitoring capability enables a proactive approach to risk diagnosis. It allows employers and healthcare professionals to respond promptly and mitigate potential harm in environments where vibration-related hazards are a significant occupational concern.

II. Literature Review

Previous research projects have studied the behavior of EMG signals during mechanical vibration exposure. For example, [9] attempted to determine whether peaks in the frequency domain of EMG signals recorded in calf muscles, found at the vibration frequency and its harmonics, could be attributed to motion artifacts or stretch reflexes. A prior study [10] assumed that these peaks resulted from motion artifacts and removed them using Chebyshev type II band-stop filters. If this assumption were incorrect, crucial information would have been mistakenly lost. To investigate this, tests using dummy electrodes—insulated from muscle signals—were performed, and the ratio of the "dummy iEMG" to the iEMG of the corresponding muscle (D/M-ratio) was calculated. EMG signal analysis showed that D/M ratios remained very low throughout the trials, with dummy signals frequently displaying a virtually flat line consisting only of background noise. A few spikes were observed, but their latencies were irregular and unsystematic. Based on these results, the researchers concluded that the primary source of the periodic electromyographic activity in the examined leg extensor muscles was most likely vibration-induced stretch reflexes.

Further research has compared how vibrations affect the EMG signals of healthy and unhealthy subjects. In particular, one study explored the effect of whole-body vibration on lower-limb EMG activity in subjects with and without spinal cord injury, showing that whole-body vibrations can elicit lower-extremity EMG activity in both non-disabled individuals and those with chronic spinal cord injury [11]. Notably, the power of the recorded EMG signal was highly dependent on vibration parameters, confirming that the choice of vibration platform and settings is critical for any clinical application of WBV. Among the parameters studied, a vibration frequency of 45 Hz with an amplitude of 1.2 mm was the most reliable combination for eliciting EMG activity in both groups. This and the previous study applied whole-body vibrations via a platform supporting the subject's weight. In contrast, the present project will focus on hand-arm vibrations, a factor highly relevant to how EMG signals change with vibration exposure, as will be shown later.

Another study examined the effects of hand-arm vibrations. Using a vibratory massager mounted vertically on a rail, it investigated how vibration therapy influences neuromuscular efficiency and EMG signal characteristics in endurance tests [12]. Trials were conducted over seven days using a massager controller with no vibration exposure, 23 Hz, and 35 Hz conditions. As previously suggested, the study aimed to understand the long-term effects of vibration therapy, meaning that immediate changes in EMG features, crucial for real-time preventive monitoring, were not evaluated.

Filtering techniques for EMG signals have been widely explored due to the critical importance of obtaining clean and reliable data for further analysis. Noise contamination can originate from multiple sources, including inherent electrode noise, movement artifacts, electromagnetic interference, muscle cross-talk, and other external factors. The challenge in filtering EMG signals arises from the significant temporal and spectral overlap between noise and the signal of interest, making it difficult to isolate and remove unwanted components [13] effectively.

One of the most commonly used filtering techniques for EMG signal processing is based on wavelet decomposition, which effectively reduces noise while preserving signal integrity. For instance, [14] utilized Daubechies (db2, db8, and db6) wavelets, as well as the orthogonal Meyer wavelet, in combination with a manual soft Min-Max thresholding method, achieving promising results in noise attenuation. A key advantage of this approach is its efficiency: wavelet decomposition captures and represents the signal's energy using only a few significant transform coefficients, reducing computational complexity while maintaining accuracy [15].

Empirical Mode Decomposition (EMD) is a relatively recent data-driven, adaptive technique for analyzing nonlinear and non-stationary data. Unlike traditional filtering approaches, EMD employs an iterative sifting process to decompose a complex signal into a finite and typically small number of components known as "Intrinsic Mode Functions" (IMFs) [16]. This method has gained popularity due to its effectiveness in processing biological signals and ease of implementation. For example, [17] proposed an EMD-based noise reduction procedure integrating EMD with a level-dependent thresholding approach, applying a soft threshold to each extracted IMF. Another study showed that this method achieved superior noise attenuation compared to wavelet-based techniques using Daubechies wavelets (db2, db3, and db4), although at the cost of increased computational time [18].

Motor Unit Action Potential (MUAP) estimation is crucial for understanding neuromuscular function and diagnosing related disorders, as it provides insights into muscle activation patterns and neuromuscular health. Recent advancements have introduced innovative methods to enhance MUAP extraction from surface electromyography (sEMG) signals, improving accuracy and computational efficiency. For instance, [19] employed a higher-order statistics-based system reconstruction algorithm to estimate the typical shape of the MUAP from an EMG signal, allowing for a more precise characterization of MUAP behavior. This approach provided a fast (real-time), cost-effective, software-based solution for visualizing MUAPs, particularly useful for clinical and research applications. Other studies, such as [20], have used artificial neural networks to classify MUAPs based on morphological and temporal features.

III. METHODOLOGY

A. Monitoring System

The monitoring system (Fig. 1) mainly aimed to acquire the EMG signals and detect vibration exposure to alert the operator. To test the system and ideally draw conclusions on how vibration amplitude, frequency, and direction affect muscle activation and fatigue, a low-cost vibration generator (Fig. 2) was built. The vibration generator was based on an electromagnetic speaker mechanism and 3D printed parts to ensure a good grip. This generator provides controlled vibration stimuli, allowing fine-tuning of frequency and amplitude via the "Generador de Frecuencia" phone app by "DCZT" available on the Play Store. The output signals were confirmed to be of the right frequency and amplitude with an oscilloscope.

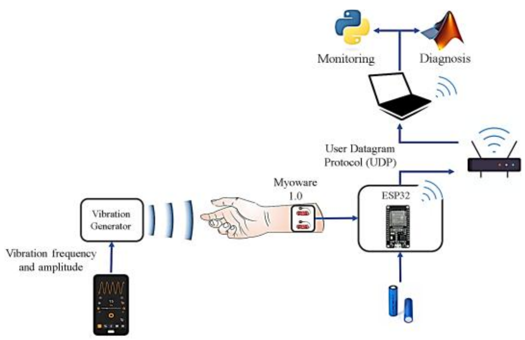


Fig. 1 Overview of the monitoring system

The EMG acquisition unit employs Myoware sensors, known for their ease of use and cost-effectiveness, with bandpass filtering and amplification circuits already built in. These sensors are connected to two targeted muscles using extension cables and adhesive electrodes to measure surface electromyographic activity. An ESP32 microcontroller was programmed to sample the EMG signals at 2 kHz, a value commonly used in related work. The microcontroller digitizes the analog signals and transmits the data wirelessly (using User Datagram Protocol for faster transmission via Wi-Fi) to a host computer to perform the signal processing. An Arduino Uno was also tested, but it struggled to sample precisely at such high rates and needed extra modules to achieve wireless communication. Given that Wi-Fi transmission already consumes considerable energy and maximising battery life was desirable, no further processing tasks were given to the ESP32. To ensure that the acquisition unit didn´t obstruct the drill operator's activities, it had to be portable, so it was powered by a 3.7 V Li-Ion battery as shown in Fig. 3.

Fig. 2 Parts design and implementation of the vibration generator

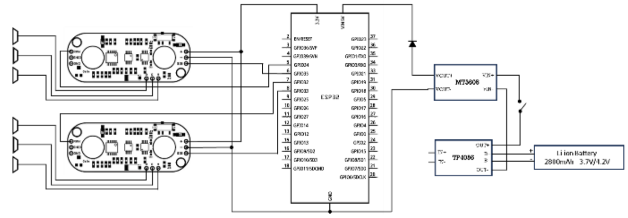


Fig. 3 Circuit diagram of the acquisition system

The EMG signals sent by the acquisition unit were processed in both real-time and non-real-time. Once the acquisition system was built and functioning correctly, sample data was recorded while experimenting with a drill. The drill was intermittently turned on and off while being forced against a rocky surface. The two monitored muscles were the Flexor Carpi Radialis (forearm) and the Biceps Brachii. During most ordinary movements, the activity patterns of these muscles are uncorrelated, as each is primarily responsible for a different motion: wrist flexion and elbow flexion, respectively. Therefore, the overall signal shapes should differ significantly unless both movements are deliberately executed simultaneously. Analyzing the EMG samples from the initial trials (Fig. 4) revealed that muscle activation levels increased upon turning on the drill, meaning this increase was registered in both muscles simultaneously.

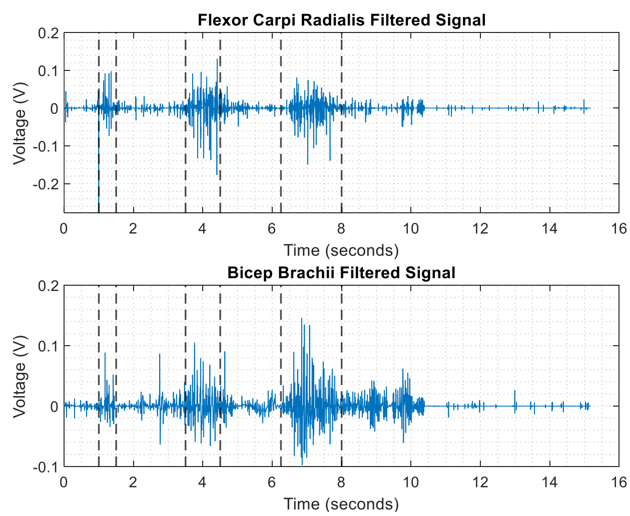


Fig. 4 EMG data from drilling trials

Based on the scenario described, a vibration detection algorithm (Fig. 5) was implemented with a Python script, which alerted the operator to see if the vibration intensity was too strong based on an increase in muscle activity registered in both arm muscles by a similar factor. A downside of the proposed algorithm is its strong dependence on properly tuning the factors and thresholds. Otherwise, it may misdetect vibrations. Implementing more robust statistical models was also evaluated; however, this would compromise both the battery life of the system and the sampling frequency, which is crucial for preserving the integrity of the EMG signal. A User Interface showing the sample signals, the exposure time, and a warning was also developed (Figs. 6 and 7).

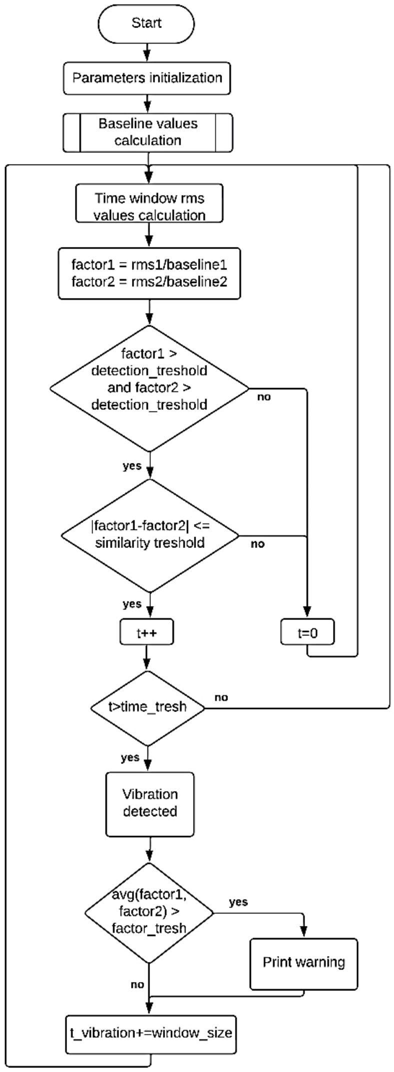
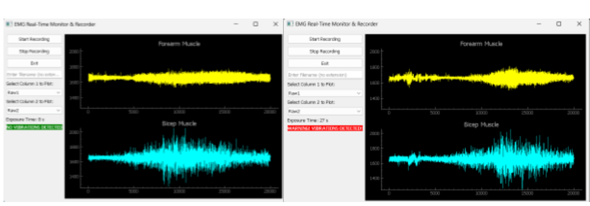


Fig. 5 Proposed vibration detection algorithm

B. Diagnosis System

Non-real-time processing included more complex and computationally demanding procedures, performed using MATLAB software. The first filter applied was an IIR Notch Filter at 60 Hz with a 3 Hz bandwidth, eliminating the Power-Line noise detected by observing a peak in the power spectrum of recorded test signals (Fig. 7). However, the signals remained noisy. Filtering EMG signals is challenging because, as mentioned before, they exist over a broad frequency band, just as white noise does, making it hard to attenuate the noise while maintaining the integrity of the EMG signal.



Figs. 6 User Interface

Several filtering techniques have been developed to address this challenge, with Wavelet Denoising and Empirical Mode Decomposition (EMD) being among the most widely used. As reviewed earlier, Wavelet Denoising separates the signal into approximation and detail coefficients using wavelet transforms, enabling targeted noise reduction. EMD, in contrast, decomposes the signal into Intrinsic Mode Functions (IMFs) via an iterative sifting process, making it suitable for analyzing non-linear and non-stationary signals. While EMD generally yields better results than wavelets, it is more computationally intensive and slower [18]. Since the diagnosis application was performed on prerecorded samples, computing time wasn't a priority, so EMD was the selected filtering method.

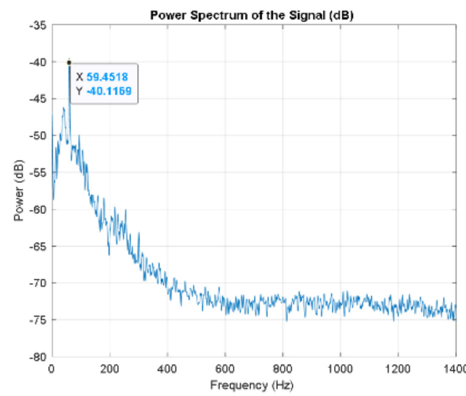


Fig. 7 Power spectrum of a raw sample signal

Signals were decomposed into 8 IMFs using the sifting algorithm. Then, a soft thresholding procedure was implemented like the one proposed by [18]. First, a visually classified as noisy segment of the signal was selected as seen in Fig. 8. Then, for each IMF, a threshold t is calculated as the standard deviation of the noisy segment times an attenuation constant, which allowed the tuning of how aggressively noise was being attenuated. Afterwards, soft thresholding is applied to each individual IMF as shown in Eq. (1)

$$t\text{IMF} = \text{sign}(\text{IMF})(|\text{IMF}| - t)_+ \quad (1)$$

where tIMFs are the filtered IMFs, and the function $(x)_+$ is defined as:

$$(x)_+ = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (2)$$

Finally, tIMFs are added, resulting in the filtered signal.

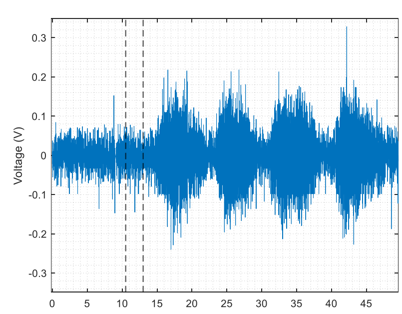


Fig. 8 Example of noise segment selection

After filtering the EMG signals, the next step was performing MUAP estimation. A MUAP is an electrical signal generated by a motor unit during muscle contraction. A motor unit consists of a single motor neuron and all the muscle fibers it innervates. When a motor neuron fires, the action potential propagates along the nerve and reaches the muscle fibers, causing them to contract. The summation of the electrical activity from all the muscle fibers in the single motor unit creates the MUAP. The summation of MUAPs from multiple motor units makes up the measured EMG signals [21]. The MatLab app developed by [22] was used in this research. It uses an efficient and unsupervised estimation algorithm, meaning the only input needed was the sample EMG signal. Its operation was verified using sample signals of a healthy and non-healthy patient, showing substantial differences between the MUAPs found in both patients (corroborating what was found in the literature).

IV. RESULTS

The monitoring system was assembled as illustrated in Fig. 9. The system uses a lithium battery, providing an approximate runtime of 8 hours of continuous data sampling and transmission. The laser cut from MDF was secured with bolts and nuts, and the electrode cables were fastened to minimize noise caused by their movement when loose. A blue LED indicates proper Wi-Fi network connectivity. Fig. 9 shows the system being carried in a backpack, leveraging its wireless functionality, and its potential application in real scenarios, such as while operating a drill. The user remains free to move their arm while real-time plotting continues uninterrupted. Additionally, real-time signal plotting is displayed, alongside a terminal interface that awaits recording initiation commands and alerts the user about potentially unsafe vibration exposure periods when detected.

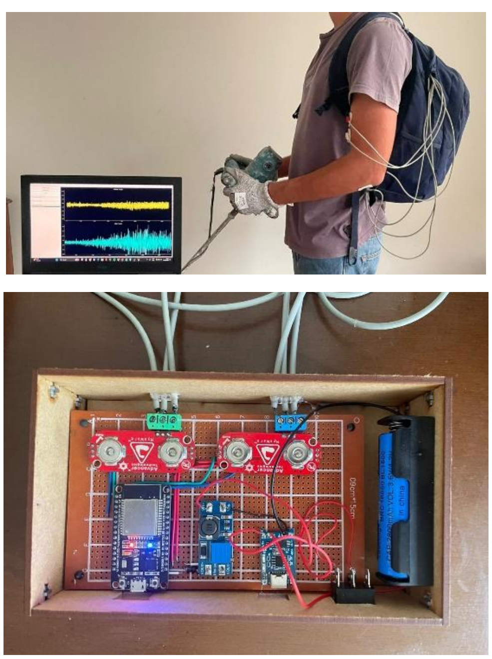


Fig. 9 Monitoring system implementation

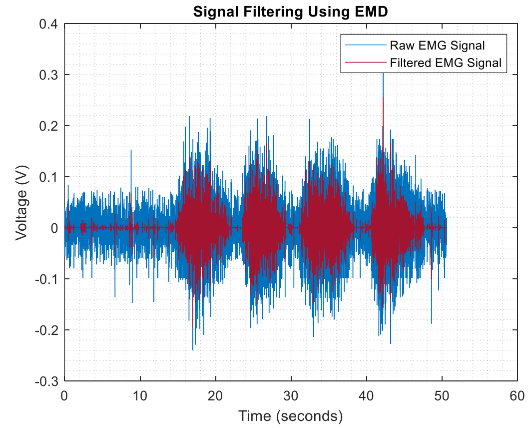


Fig. 10 Signal filtering results

Unexpected results were observed regarding the vibration generator. Even with the finalized system, which achieved substantially improved signal quality, vibration presence could not be detected. After each trial, the signals appeared identical before and after contact with the vibrating object. This finding contrasts with previous studies showing that vibration exposure increases muscle activity. Upon reviewing the literature, it was determined that most prior research primarily focused on monitoring leg muscles under whole-body vibration, typically transmitted via the feet using a vibrating platform. Detecting muscle activation in such cases is logical, as the body attempts to balance and counteract these movements. None of the research articles reviewed mentioned this, likely due to the predominance of studies on vibration therapy, where vibrations are typically transmitted through the feet. Unfortunately, the constructed vibration generator couldn't support a person's weight, preventing the replication of these conditions. However, this outcome provided crucial insights into scenarios where muscle activity increases, suggesting muscle activation arises from exposure to vibrations and the body's efforts to compensate for such stimuli. The drilling trials' results endorsed this idea.

After fine-tuning the parameters, the proposed algorithm detected vibrations in 73 of 100 exposure segments. More robust, adaptive, and accurate alternatives should be tested for better results. As mentioned earlier, implementing more advanced models would not be feasible with low-cost signal acquisition hardware without compromising key aspects essential for preserving signal integrity.

MatLab-based signal processing filtered previously recorded signals, preserving relevant peak and valley information while substantially reducing noise as visually evidenced in Fig. 9. Utilizing the Signal to Noise Ratio (SNR) calculation method proposed by [23], it was verified that the SNR was consistently increased by more than 120% when applying the proposed filtering process. Additionally, the MUAP application functioned correctly with filtered signals (Fig. 11). Due to time constraints set for this project, the MUAP estimation tool wasn't tested on a subject affected by vibration-induced disorders, but as mentioned, it is widely accepted that MUAPs are an indicator of muscle health.

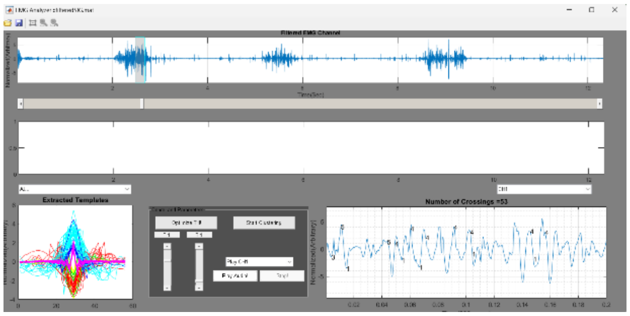


Fig. 11 MUAP estimation tool used on filtered signal

V. Conclusion

The developed monitoring system integrated MyoWare sensors, an ESP32 microcontroller, and a wireless data transmission mechanism to provide real-time feedback on muscle activity and vibration exposure. The acquisition system demonstrated portability, ease of use, and robustness during testing, with continuous operation sustained for up to 8 hours on a lithium battery. However, the vibration generator faced limitations in replicating conditions commonly studied in literature, which typically involve whole-body vibrations transmitted through weight-bearing platforms, preventing more rigorous system testing. This highlighted the critical role of compensatory body mechanics in muscle activation during vibration exposure, suggesting that further testing should be done with robust platforms to replicate these conditions better.

An initial vibration detection algorithm was proposed. Although it performed well in most cases, it had notable limitations regarding robustness and accuracy. For example, it relied heavily on manual parameter tuning. It occasionally failed to correctly detect the presence of vibrations in certain situations because of the noise present (the filtering techniques were applied offline). Upgrading the hardware could enable more robust and adaptive models capable of processing signals in real time without compromising the sampling rate and battery life. Future research should also evaluate and compare the effectiveness of these improved detection methods.

The diagnosis system utilized different signal processing techniques to enhance EMG signal quality and extract meaningful data for analysis. By employing Empirical Mode Decomposition (EMD) for noise reduction, the system achieved significant improvements in the Signal-to-Noise Ratio (SNR), effectively preserving critical EMG signal features necessary for accurate interpretation. Although time constraints limited testing on subjects with vibration-induced disorders, the system successfully performed Motor Unit Action Potential (MUAP) estimation, demonstrating its potential for diagnostic applications. Further work should prioritize analyzing the estimated MUAPs in greater depth. The authors recommend exploring the application of Artificial Neural Networks (ANNs) to identify patterns within MUAPs, which could help draw actionable conclusions.

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