Comparison of Mechanomyogram Signals Using an Accelerometer and a Condenser Microphone during Isometric and Concentric Contractions of the Biceps Brachii Muscle

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Abstract

According to the evaluation of muscle function during static exercise using a microphone and an acceleration sensor, accelerometers are more likely to be affected by motion artifacts than microphones. Additionally, microphones are less likely to be affected by motion artifacts compared to accelerometers. In this study, motion artifacts were analyzed using both an accelerometer and a microphone. As a result of conducting a variance analysis of the three factors—muscle exertion, velocity, and elbow joint angle—significant differences were found in all factors (muscle exertion, velocity, and elbow joint angle) in the MMG signals obtained using a microphone ($p < 0.001$). Furthermore, a significant interaction effect was found between velocity and elbow joint angle ($p < 0.001$). It is suggested that the low-frequency components of the PSD of the MMG are reduced by increased muscle strength during exertion. However, during dynamic exercise, the low-frequency components of the MMG signals recorded with the accelerometer (MMGacc) significantly increased. Considering the frequency characteristics observed in this study, it is concluded that the accelerometer is more likely to capture motion artifacts in the MMGacc signals within the frequency range of 5 to 10 Hz.

Keywords: Electromyogram (EMG), Mechanomyogram (MMG), Power spectral density (PSD), Biceps Brachii Muscle

1. Introduction

Electromyography (EMG) and Mechanomyography (MMG) are widely used to assess the functional state of muscles [1]. EMG measures the electrical signals generated by muscles during activity, enabling the evaluation of muscle fatigue, strength, and various neuromuscular disorders, thereby proving useful for monitoring muscle function recovery [2]. MMG, on the other hand, measures the subtle vibrations produced during muscle contraction, assessing the mechanical response of muscles. As such, MMG provides valuable information on muscle activation patterns, fatigue, and various muscle-related diseases. When used in conjunction with EMG, MMG offers more precise insights into the functional state of muscles [3]. These diagnostic tools play a crucial role in diagnosing and treating muscle disorders as well as in developing personalized training programs [4].

However, the presence of motion artifacts can affect the accuracy of signal measurements in non-invasive muscle assessment technologies. Motion artifacts may arise due to movements of the muscle being measured, adjacent muscles, or other body parts, resulting in the inclusion of unrelated data in the measurement, which can compromise the accuracy of interpretation. To address this issue, technical approaches are required to minimize motion artifacts. One approach involves the use of signal processing techniques, which employ advanced filtering methods and algorithms to remove noise, thereby extracting cleaner muscle activity signals. Another approach involves optimizing the placement and fixation of the measurement equipment to reduce the effects of movement, a particularly important consideration in dynamic measurement environments [5–6].

MMG has been found to be more sensitive than EMG in detecting age-related muscle atrophy, indicating its potential for identifying subtle changes in muscle function [7]. For example, an MMG-based muscle strength monitoring tool for long COVID patients highlights the importance of sensor placement and contact pressure in reducing measurement artifacts [8].

This study focuses on the comparison of Mechanomyogram (MMG) signals obtained using an accelerometer and a condenser microphone during isometric and concentric contractions of the biceps brachii muscle.

2. Related Works

At the paper, Hand Gesture Recognition Using Compact CNN via Surface Electromyography Signals, Lin Chen et al. explored the use of surface electromyography (sEMG) signals for hand gesture recognition. The researchers developed a compact convolutional neural network (CNN) model to extract hidden features from sEMG signals, enabling the prediction of human motion intentions. The model was validated on two datasets, achieving high classification accuracy. While the focus is on sEMG, the methodologies for signal processing and gesture recognition are relevant to MMG studies [9].

At the paper, The Control and Perception of Antagonist Muscle Action, Mark L. Latash examined the role of antagonist muscles in movement control, discussing how these muscles contribute to stopping movements and providing necessary levels of mechanical characteristics for fast actions. It delves into the neural control of antagonist muscles and their perception, offering insights into muscle activation patterns that are pertinent to MMG research [10].

At the paper, Mechanomyography and Muscle Function Assessment: A Review of current state and prospects, Morufu Olusola Ibitoye et. al. focused on the applications of MMG in assessing muscle function. It discusses various MMG signal acquisition methods, including the use of accelerometers and microphones, and evaluates their effectiveness during different types of muscle contractions. The paper also addresses challenges such as motion artifacts and suggests techniques for minimizing their impact on MMG signal accuracy [11].

Md. Anamul Islam et. al.’s paper, Mechanomyography Sensor Development, Related Signal Processing, and Applications: A Systematic Review, aimed to determine the current status of MMG in sensor development, related signal processing, and applications. Six electronic databases were extensively searched for potentially eligible studies published between 2003 and 2012. From a total of 175 citations, 119 were selected for full-text evaluation and 86 potential studies were identified for further analysis [12].

3. Research Methodology

The target muscles for this study were the biceps of the right upper arm, and the experiment was conducted on 10 healthy adult males (mean age: 23.5 ± 0.8 years) using the device shown in Figure 1. For the measurements, the maximal voluntary contraction (MVC) at a 90-degree elbow joint angle was first measured. As part of the static exercise experiment, the elbow joint angle was held stationary for 5 seconds at every 10-degree increment within the range of 40 to 140 degrees, under loads of 20% and 40% MVC.

This procedure was repeated three times for each load condition. For the dynamic exercise experiment, right arm flexion was performed three times without pausing, within the elbow joint angle range of 40 to 140 degrees. The load conditions were set at 20% and 40% MVC, and the velocity of flexion was measured under four conditions: 10 degrees/second and 20 degrees/second.

In the MMG (MMGacc) measurements using an acceleration sensor, the acceleration sensor (9G111BW; apparent dimensions: 4 × 4 × 13 mm, mass: 1.3 g) was attached to the subject’s muscle with double-sided tape. The signal was amplified using an amplifier for piezoelectric transducers, with a frequency band of 0–1 kHz and an amplification factor of 1000.

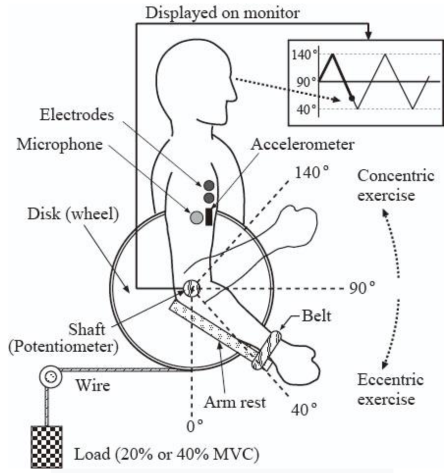


Figure 1 Experimental apparatus

For MMG (MMGacc) measurements using a microphone, a microphone (EM246; diameter: 5.8 mm, height: 2.1 mm, mass: 0.2 g) was mounted in a case with an air chamber (diameter: 10 mm, height: 5 mm) and attached in the same manner as the accelerometer to measure MMG.

To compare with MMG, electromyography (EMG) was also measured using bipolar induction with two pairs of cup electrodes (diameter: 8 mm) attached approximately 1 cm apart. The measured signal was amplified using a multi-channel amplifier with a frequency band of 5–300 Hz and an amplification ratio of 1000. The amplified signal was then AD-converted at a sampling frequency of 1 kHz and stored on a PC. For MMG, a high-pass digital filter of 2 Hz was applied.

Considering the influence of motion artifacts, signal processing for the MMG measurements obtained via acceleration sensors and microphones was performed in the same way. The measured signal was analyzed using the root mean square (RMS) to provide amplitude information, with the interpretation interval defined as 3 seconds of stable muscle contraction for every 10 degrees of elbow joint angle from 40 to 140 degrees during static exercise. In dynamic exercise, the RMS was calculated for each 10-degree analysis interval within the elbow joint angle range of 40 to 140 degrees. The RMS values were evaluated as relative values (% RMS) compared to the RMS obtained during maximum exertion.

Additionally, Fourier transform was performed, and power spectral density (PSD) and median power frequency (MDF) were calculated using the same interpretation intervals as for RMS. The calculations utilized Hamming's window function, with an FFT size of 1024, the number of data points, and 50% overlap. To examine motion artifacts in MMG, the spectrum—representing the energy distribution from the Fourier transform—was used alongside time-frequency analysis. The spectrum is expressed by the following formula:

$$X(t_0, O) = \left|\int_{-\infty}^{\infty} x(t)w(t-t_0, dt)\ exp\ exp\ (-jOt)\ dt\right|^2 \quad (1)$$

$X(t_0, O)$ is the spectrum for time t_0, x(t) is the input signal, $w(t-t_0, dt)$ is the window function, and dt is the window length. For the obtained power spectrum, the ratio of energy in each frequency band, 5Hz to 10Hz, 10Hz to 15Hz, 15Hz to 20Hz, 20 Hz to 25Hz, and 25Hz to 30Hz [13-15], is calculated. The equations for the distribution of each frequency band are as follows.

$$\frac{\int_5^{10} X(t_0, f)df}{\int_5^{30} X(t_0, f)df} \quad (2),$$

$$\frac{\int_{10}^{15} X(t_0, f)df}{\int_5^{30} X(t_0, f)df} \quad (3),$$

$$\frac{\int_{15}^{20} X(t_0, f)df}{\int_5^{30} X(t_0, f)df} \quad (4)$$

$$\frac{\int_{20}^{25} X(t_0, f)df}{\int_5^{30} X(t_0, f)df} \quad (5),$$

$$\frac{\int_{25}^{30} X(t_0, f)df}{\int_5^{30} X(t_0, f)df} \quad (6)$$

It represents the ratio of the sum of the power spectrum values to the entire sum of the power spectrum of each frequency band. A t-test was performed on the difference in exerted muscle using this power spectrum ratio.

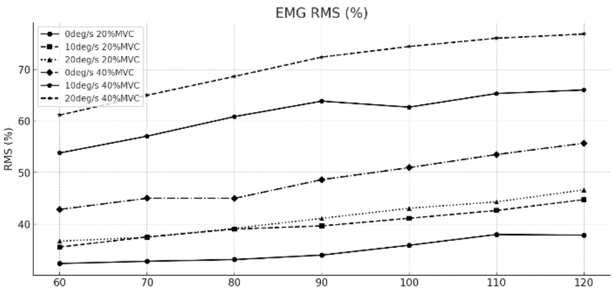
4. Simulation and Results

Figure 2 shows the average of the %RMS across all subjects. The %RMS was calculated for the value at maximal exerted muscle. Analyses of variance were conducted for the exerted muscle, velocity, and elbow joint angle.

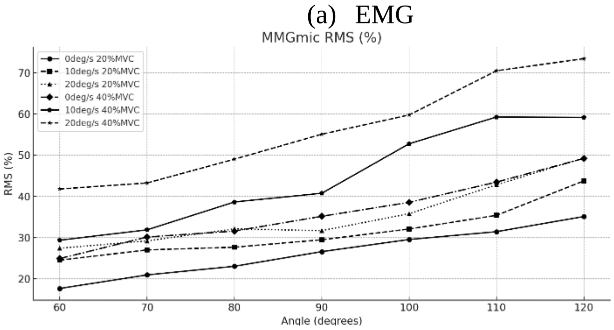
As a result, significant differences were found in EMG for all exerted muscles, velocity, and elbow joint angle($F(1,9) = 191.136$, $p < 0.001$, $F(2,18) = 33,135$, $p < 0.001$, $F(6,54) = 127.833$, $p < 0.001$).

In the MMG using a microphone, significant differences were found in all factors of the exerted muscle, velocity, and elbow joint angle($F(1,9) = 107.615$, $p < 0.001$, $F(2,18) = 24.664$, $p < 0.05$, $F(6,54) = 44.270$, $p < 0.001$). The MMG using an acceleration sensor showed a significant difference in the factors of muscle and velocity ($F(1,9) = 117.141$, $p < 0.001$, $F(2,18) = 38.601$, $p < 0.001$).

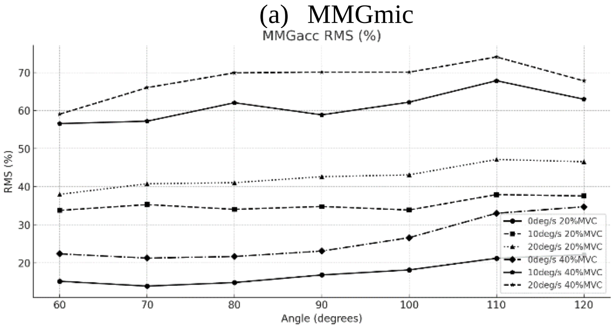
RMS increased with the exerted muscle strength, velocity, and elbow joint angle, as well as with EMG and MMG. In both EMG and MMG using a microphone, RMS increased with the elbow joint angle for each level of exerted muscle strength. However, in MMG measured using an acceleration sensor, the increase in RMS with elbow joint angle was not as significant as that observed in EMG and MMG using a microphone.



(a) EMG



(a) MMGmic



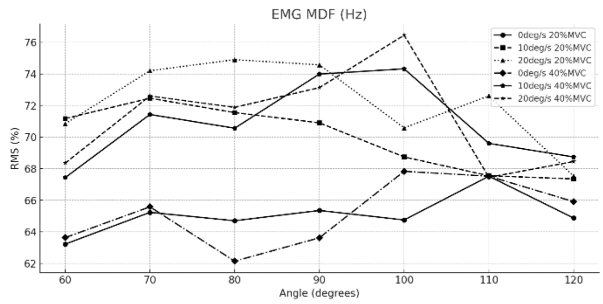
(b) MMGacc

Figure 2 RMS of EMG and MMG

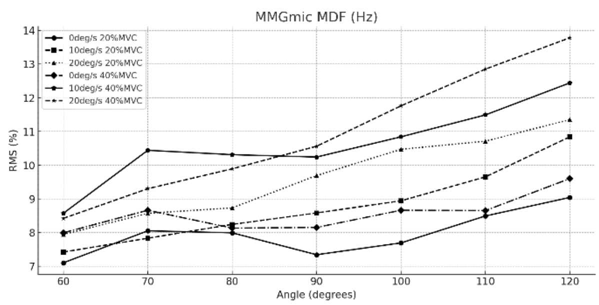
Figure 3 shows the average values for MDF. There was no significant change in MDF for EMG due to changes in the exerted muscle strength, velocity, or elbow joint angle. However, in the MMG measured using a microphone, MDF increased with the exerted muscle strength, velocity, and elbow joint angle. In the MMG measured using an accelerometer, MDF increased with velocity, but no significant increase was observed with exerted muscle strength or elbow joint angle.

Variance analysis of the three factors—exerted muscle strength, velocity, and elbow joint angle—revealed significant differences in all three factors for the MMG measured using a microphone ($F(1,9) = 8.738$, $p < 0.05$; $F(2,18) = 17.419$, $p < 0.001$; $F(6,54) = 28.440$, $p < 0.001$). Additionally, a significant interaction was found between velocity and elbow joint angle ($F(12,108) = 4.611$, $p < 0.001$).

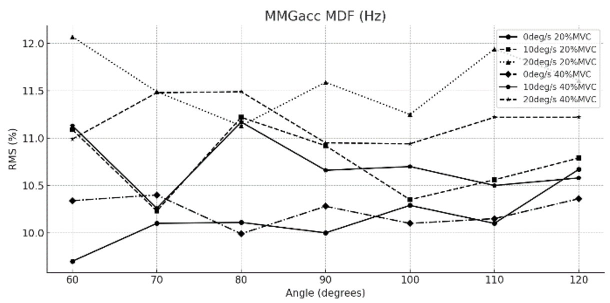
For the MMG measured using an accelerometer, only velocity showed a significant difference ($F(2,18) = 8.653$, $p < 0.001$).



(a) EMG



(b) MMGmicc



(c) MMGacc

Figure 3 MDF of EMG and MMG

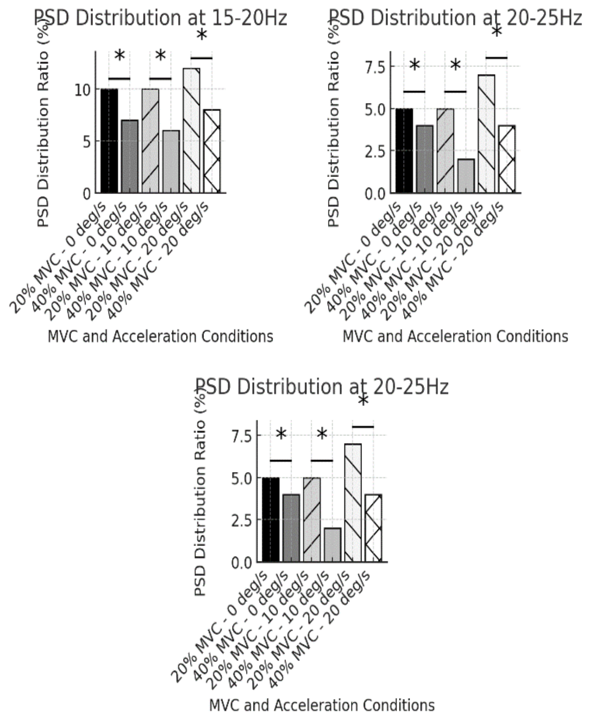
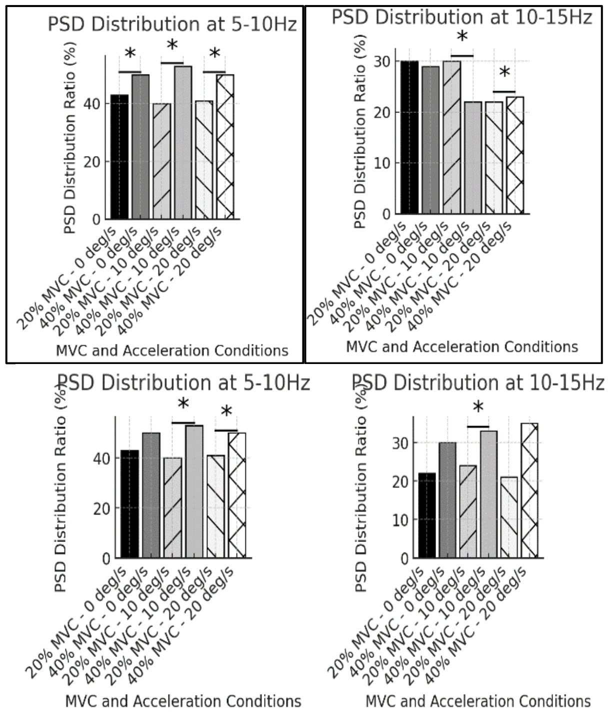


Figure 4 PSD distribution ratio of the microphone



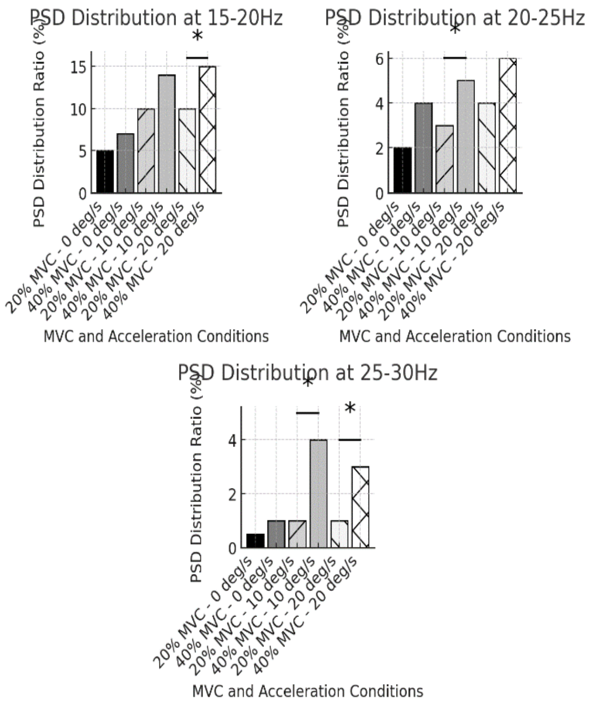


Figure 5 PSD distribution ratio of acceleration sensor

Figure 4 shows the power spectral density (PSD) distribution ratio of the MMG signals recorded using a microphone. This figure highlights how signal energy is distributed across different frequency bands, such as 5–10 Hz, 10–15 Hz, and so on. The distribution ratio illustrates that signals captured with the microphone have reduced motion artifact interference, especially in lower frequency bands. This makes the microphone a more reliable sensor for measuring muscle activity under varying conditions. Figure 5 illustrates the PSD distribution ratio for MMG signals measured using an accelerometer. Unlike the microphone data, this figure demonstrates that signals obtained through the accelerometer are more susceptible to motion artifacts, particularly within the low-frequency range of 5–10 Hz. This result suggests that accelerometers might introduce more noise into the data, making them less effective for accurately capturing muscle responses compared to microphones.

Together, Figures 4 and 5 compare the sensitivity of microphones and accelerometers to motion artifacts. The results underscore the microphone's advantage in producing cleaner and more reliable MMG data.

5. Conclusion

This study employed accelerometers and microphones to evaluate muscle function during static and dynamic exercises and analyzed the impact of motion artifacts during these processes. The responses of the two types of sensors under each condition and the influence of motion artifacts on the measurement data were elucidated. Results from RMS and MDF analyses of the mechanomyogram using a microphone (MMGmic) and an accelerometer (MMGacc) indicated that in MMGmic, RMS significantly increased with an increase in muscle exertion, velocity, and elbow joint angle [16-19]. This demonstrates that MMGmic accurately reflects muscle exertion and mechanical responses using a microphone.

In contrast, in MMGacc, a significant increase in RMS was observed only with muscle exertion and velocity, while changes in RMS were not significant with changes in elbow joint angle. This suggests that accelerometers may be more susceptible to the influence of motion artifacts than microphones.

In the MDF analysis, MMGmic also exhibited a significant increase in MDF with increased muscle exertion, velocity, and elbow joint angle, indicating that MMGmic is more sensitive for assessing muscle fatigue and responsiveness using a microphone. However, in MMGacc, an increase in MDF was observed with velocity, but no significant changes were noted with muscle exertion or elbow joint angle [20][21].

The analysis of the three factors (muscle exertion, velocity, and elbow joint angle) showed significant differences in all factors for MMGmic, including the first-order interaction between velocity and elbow joint angle [22]. In contrast, MMGacc showed significant differences only with velocity. This confirms that MMGmic provides more consistent and reliable data across various exercise conditions than MMGacc [23].

This study verified the effects of motion artifacts on mechanomyogram measurements using accelerometers and microphones. In particular, MMGmic appears to be less affected by motion artifacts than MMGacc, suggesting its potential for a more accurate assessment of mechanical responses in muscles [24][25]. These findings contribute to the advancement of non-invasive muscle assessment technologies and serve as crucial reference material for monitoring training effects in athletes, evaluating rehabilitation processes, and diagnosing neuromuscular diseases [26]. Furthermore, compared to previous studies, this study proposes new approaches to minimize motion artifacts, thereby enhancing the accuracy of muscle function assessments [27]. These results can serve as a foundation for improving the reliability of non-invasive muscle assessment technologies and expanding their applicability in various clinical and sports science fields [28][29].

Future studies, including more subjects and a variety of exercise conditions, can contribute to more comprehensive and generalized results. Further advancements in sensor technology and signal processing algorithms are required to effectively reduce the impact of motion artifacts. Such developments will enhance the accuracy and reliability of muscle function assessments.

6. References

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