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Quantitative Measurement of Muscle Spasticity for Neurological Disorders Using Mechanomyography: A Statistical Analysis

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ABSTRACT

Spasticity, a common sign of upper motor neuron syndrome, affects conditions such as stroke, cerebral palsy, traumatic brain injury, and spinal cord injury. The Modified Ashworth Scale (MAS) is widely used by therapists to evaluate spasticity during passive flexion to the appropriate joints of limbs according to the level of muscle resistance, but its reliance on subjective judgment can lead to inconsistent assessments and impact rehabilitation strategies. This study introduces Mechanomyography (MMG) as a quantitative approach for assessing spasticity in the forearm muscles of 30 patients (29 stroke, 1 cerebral palsy), with ethical approval and informed consent. Before feature extraction, the data underwent thorough pre-processing, yielding a dataset of 48 features derived from the x, y, and z axes in three dimensions, representing the longitudinal, lateral, and transverse orientations of biceps and triceps muscle fibers. The extracted features were subjected to statistical analyses, including linear regression, Pearson correlation, and one-way MANOVA, to examine the relationship between MMG signal features with muscle spasticity levels as quantified through the MAS. Linear regression showed a significant positive association ($R = 0.881$, $F(41,48) = 4.076$, $p < 0.001$), with MMG features contributing 77.7% of MAS variability ($R^2 = 0.777$). Pearson correlation revealed strong associations, with $Miny_1$ negatively correlated ($r = -0.542$) and $RMSy_1$ positively correlated ($r = 0.515$). Additionally, one-way MANOVA confirmed significant differences in MMG features across MAS levels, validating their relevance in spasticity assessment. These results establish MMG as a reliable, objective tool for spasticity evaluation, advancing beyond traditional subjective methods.

Keywords: Spasticity; Mechanomyography; Modified Ashworth Scale; Linear Regression; Pearson Correlation; MANOVA

INTRODUCTION

The musculature is a vital component of the human body and can be harmed easily due to some factors such as accidents, fatigue, inflammation, diseases, infections, and the negative effects of certain illicit substances (Daud et al. 2024). At the same time, muscles can also be affected by various problems and illnesses, resulting in weakness, pain, and impaired movement, or even paralysis which can contribute to muscle spasticity (Aliff et al. 2023). Spasticity is an identifiable sign of upper motor neuron syndrome, a neurological illness observed across multiple diseases which include amyotrophic lateral sclerosis, brain damage, cerebral palsy, stroke, and spinal cord injury (Shaikh et al. 2024; Spieker et al. 2024). Frequent observation of spasticity appears in the upper extremities, with a higher incidence in the forearm (79%), wrist (66%), and shoulder (58%) (Bavikatte et al. 2021). Additionally, stroke is acknowledged as the second leading reason for death followed by the main source of disability globally, making it the third largest contributor to both mortality and disability worldwide (Feigin et al. 2022; Kim et al. 2021; Starosta et al. 2024). In 1980, Lance utilised the term "spasticity" when referring to a motor disorder called upper motor neurone syndrome (Facciorusso et al. 2024; Lance 1980; Whitten et al. 2024). This disorder is defined through heightened muscle tone along with more severe tendon jerks, which are affected by the speed of movement and result from the excessive activation of the stretch reflex (Takeuchi et al. 2024).

The Australian Spasticity Assessment Scale (ASAS) and the Modified Ashworth Scale (MAS) are considered the most trustworthy tools for evaluating spasticity throughout the clinical settings (Wang et al. 2022; Yu et al. 2020). The MAS is very commonly used in stroke rehabilitation regimens. At the same time, this conventional method has been known as a subjective measurement by therapists and commonly shows the inconsistency measurement throughout the assessment (Erden et al. 2020). Typically, the assessment requires therapists performing passive movements to assess the degree of muscle resistance during passive stretching and assigning spasticity grades accordingly (Fujimura et al. 2022; Santos et al. 2017). Aside from the MAS and ASAS, other clinical instruments employed for evaluating spasticity encompass the Fugl-Meyer Assessment (FMA), the Modified Tardieu Scale (MTS), the Spinal Cord Assessment Tool for Spastic Reflexes (SCATS), and the Penn Spasm Frequency Scale (PSFS) (Billington, Henke & Gater 2022; Luo et al. 2019). Electromyography (EMG), an approach employed for the measurement of electrical muscle activity, is currently limited to therapeutic purposes and susceptible to interruption caused by noise and variations in resistance, therefore turning it inefficient for several circumstances (Correa et al. 2023; Jun et al. 2018; Lewandowska-Sroka et al. 2021). Mechanomyography (MMG) is a recently developed non-invasive method for measuring mechanical muscle activity (Turnsek & Paravlic 2024). This technique has advanced from detecting basic muscle vibrations to a sophisticated tool capable of accurately tracking changes in muscle fiber morphology during contractions. It specifically monitors lateral movements produced by active muscles and their inherent vibration frequencies. MMG represents a technique that can be used as an alternative to EMG to quantify muscle vibrations as well as mechanical activity produced by functional muscles (Meagher et al. 2020; dos Santos et al. 2024). It is achieved by utilisation of sensors such as microphones or accelerometers. Piezoelectric sensors, microphones, and accelerometers enable effective detection of low-frequency MMG signals from skeletal muscles, despite susceptibility to electrical noise (Hazem, Soubra & Othman 2023; Uwamahoro, Sundaraj & Subramaniam 2021). MMG is better than EMG due to its ability to effectively react to skin conditions and consistently function in changing circumstances. (Castillo et al. 2021). It minimises requirements for repeated sanitation and upkeep of optimum skin conditions while in functioning.

The primary aim for this study is to investigate the MMG signal's ability to provide an objective assessment of muscle spasticity through the implementation of an appropriate statistical tests. The study focusses on extracting and analysing time domain features through MMG signals, which are subsequently examined using these statistical tests. The article is structured in a particular manner: Section 2 presents a comprehensive summary of research conducted on the topic over the years. Section 3 provides a comprehensive account of the patient selection, experimental configuration, along with the data preprocessing and analysis approach. Section 4 explains the statistical tests result on the relationship between MMG signal features and MAS level. Section 5 presents and discusses the experimental findings, followed by a subsequent section explaining the conclusions drawn from the study.

RELATED WORKS

Several studies utilised statistical analysis to investigate muscle spasticity by analysing data from wearable sensors in order to discover notable values that may be used to represent the research findings. This section reviews studies that have employed statistical analysis to explore muscle

spasticity using data from wearable sensors, aiming to identify significant metrics for representing research findings in this field.

E. L. Santos et al. 2016 examined the correlation between various degrees of spasms, as evaluated through the Modified Ashworth Scale (MAS) and both duration and spectrum properties of Mechanomyography (MMG) pulses. MMG features included median energy (MMG_{ME}) in the time domain and median frequency (MMG_{MF}) in the frequency domain. The Kruskal-Wallis test revealed significant differences in MAS spasticity levels for MMGME, with a robust positive linear correlation between MMGME and MAS (R^2 = 0.9557, Pearson correlation coefficient = 0.9856, $p < 0.001$). Spectrum analysis indicated no significant changes in MMG_{MF} between different MAS spasticity levels (Kruskal-Wallis p = 0.0059). The connection between MAS and MMG_{MF} was moderately linear ($R^2 = 0.4883$) and statistically significant (Spearman $p < 0.001$, correlation coefficient 0.4590). These findings indicate that MMG_{ME} represents a highly accurate measure of spasticity, with significant variations shown among different degrees of MAS. On the other hand, median frequency (MMG_{MF}) showed a moderate linear correlation with MAS and had fewer significant variations among different levels of spasticity.

H. Wang et al. 2017 conducted an investigation into the utilisation of support vector machine (SVM) techniques in conjunction with surface electromyography (sEMG) and mechanomyography (MMG) sensors to objectively evaluate elbow spasticity. In this study, features from both sEMG and MMG signals were extracted, including mean power frequency (MPF), median frequency (MF), and root mean square (RMS). The connection across these features and the severity of spasm has been evaluated by Spearman correlation analysis. The results showed a significant association ($p < 0.05$) between biceps (MMG-RMS, EMG-RMS) and triceps (MMG-RMS, EMG-RMS, EMG-MPF). The study revealed notable correlations between the degree of spasticity and specific features derived from both sEMG and MMG signals, namely RMS numerical values for both biceps and triceps muscles. In clinical settings, these results emphasize the possibility of using these signal characteristics, particularly MMG-RMS and EMG-RMS, as dependable indications for evaluating the degree of spasticity.

Besides that, Jun et al. 2018 assessed spasticity using Mechanomyography (MMG) sensor among individuals with brain injury, stressing objective clinical evaluation. The Kendall rank correlation test was employed to statistically compare the measurements of MAS across three clinicians. The MMG ratio, denoted as the normalized hull area, was used to measure the triaxial movement of the agonist muscle compared to the antagonist muscle. The MMG signal ratio was employed for contrasting the spastic sides of the limb using the Mann-Whitney test and Spearman correlation test. While all patients exhibited spasticity, most physicians‘ concordance coefficients were not statistically notable. The normalized hull area ratio in MMG demonstrated a significant difference between normal and spastic muscles (p = 0.01). Additionally, a substantial correlation was observed between the normalized hull area ratio and the mean MAS, with a correlation coefficient of r = 0.69 and a significance level of p = 0.01. The findings highlight the relevance of MMG providing more independent tool for assessing muscle spasticity, therefore offering more reliable and consistent data in comparison to conventional clinical assessments.

Esposito et al. 2018 conducted research on a force-sensitive resistor (FSR) with the aim of developing a non-invasive sensor that can accurately measure the contraction of muscles. A comparative analysis was conducted between the FSR signal and Electromyography (EMG) to evaluate the efficacy of Mechanomyography in quantifying vibration during muscle contraction. The calibration result of FSR indicates the regression line has an angle coefficient of 0.855 and a coefficient of determination R^2 of 0.99 for the linear regression data, indicating a strong fit. The association between the maximal voluntary contractions of patients‘ flexor carpi ulnaris muscles and the corresponding EMG linear envelope (EMG-LE) was analysed by determining Pearson‘s correlation coefficients. The Pearson‘s correlation coefficient „r“ was used to quantify the similarity between the two signals. The estimated result was 0.9286, with a p-value of less than 0.001 (two-tailed test). The EMG linear envelope (LE) showed a high association with the FSR force signal. Nevertheless, there was a distinguishable time lag in the force signal compared to the EMG recorded at the end of each contraction. The delay seen was most likely caused by the electromechanical delay, which has a tendency to amplify during muscular relaxation. The statistical analysis demonstrates a strong and trustworthy relationship among the FSR output and the EMG linear envelope. The Pearson‘s correlation values frequently surpass 0.9, indicating a dependable comparison between the two measurements.

In addition, Puzi et al. 2019, 2020 investigated the development of an Automatic muscular Spasticity Assessment System (AMSAS) which equipped with torque sensor to measure the degree of muscular spasticity and the potentiometer in measuring the elbow joint angle during the assessment. A one-way ANOVA with a significance level of $p < 0.05$ was used to identify important characteristics that suggest muscle spasticity. Among the seven features analyzed, four were selected: total work done for the first half of the region (TWD1), total work

done for the second half of the region (TWD2), catch position (P_c), and stiffness of post-catch (K_{post}). The *p*-value was utilized to assess the statistical significance of differences in the dependent variables. The incorporation of features gained from system, along with statistical testing provided a more objective and quantitative evaluation of muscle spasticity levels using the MAS assessment tool.

Furthermore, Scarborough et al. 2023 explored the use of a conductive electroactive polymer sensor as an innovative wearable surface mechanomyography (sMMG) sensor for quantifying muscle contractions and dynamometry measures of force output. The study compared the accuracy of the sensor with surface electromyography (sEMG). The study employed ANOVA to assess the duration of total contraction of the quadriceps, hamstrings, and gastrocnemius muscles during parallel squat and maximal voluntary isometric contractions (MVIC) exercises, as determined by sMMG and sEMG. The associations between contraction durations acquired from sMMG, sEMG, and dynamometry force output were evaluated using Pearson correlation analysis with a prescribed significance level of $p < 0.05$. Significant associations were seen between the duration of the sMMG signal and the sEMG signal, as well as with the force production measured by a handheld dynamometer during MVIC of the quadriceps, hamstrings, and gastrocnemius muscles. More precisely, the sMMG signal exhibited a significant association with the length of the sEMG signal for the quadriceps ($r = 0.970$), hamstrings ($r = 0.958$), and gastrocnemius ($r = 0.979$) muscles. Moreover, there was a significant positive connection between the duration of the sMMG signal and the force production measured by the handheld dynamometer for the quadriceps ($r = 0.906$) and hamstrings ($r = 0.856$). A modest correlation was found for the gastrocnemius ($r = 0.728$). The alignment of raw data signals across all three measuring devices provides additional evidence for these conclusions. Similar data output patterns were seen between the sMMG and sEMG signals during a parallel squat, with a strong correlation between the entire time of quadriceps contraction identified by both modalities (sEMG: mean = 2.526 ± 0.519 s; sMMG: mean = 2.489 ± 0.504 s; $r = 0.822$, $p < 0.001$). The strong positive correlations between the length of sMMG signals and force generation suggest that sMMG can serve as a reliable method for evaluating muscle force output. The consistency of data patterns among several measuring devices provides additional evidence for the reliability of sMMG as a supplementary approach to sEMG in assessing muscle function.

Overall, these findings indicate that combining data from wearable sensors with advanced statistical methods can improve the precision and impartiality of evaluations of spasticity. This offers useful resources for both clinical applications and research purposes.

METHODOLOGY

PATIENTS SELECTION AND EXPERIMENTAL SETUP

A total of 30 patients with upper limb spasticity were enrolled in the study, with 29 being post-stroke patients and one diagnosed with cerebral palsy. The study was conducted at Sultan Ahmad Shah Medical Centre (SASMEC) and the National Stroke Association of Malaysia (NASAM). The study received ethical approval from the Research Ethics Committee of the International Islamic University Malaysia (IIUM), referenced under IREC 2023-025, prior to its commencement. Patients were selected based on a diagnosis of upper limb spasticity and were within the age range of 18 to 80 years. All patients provided informed consent and were classified based on their Modified Ashworth Scale (MAS) levels which range from 0, 1, 1+, 2, and 3. Patients at MAS level 4 were excluded from this study due to their severe spasticity, which causes the afflicted muscles to be rigid in either flexion or extension, exhibiting no discernible range of motion during passive movement. This rigidity hinders the evaluation of dynamic muscle responses essential for MMG signal capture and feature extraction, as the vibrations and mechanical activity of the muscles cannot be accurately monitored or analysed in this condition.

Table 1 summarizes the demographic characteristics of the patients, categorized as follows: MAS 0 (5 patients), MAS 1 (16 patients), MAS 1+ (3 patients), MAS 2 (4 patients), and MAS 3 (2 patients). This classification allowed for a structured analysis of muscle spasticity across varying levels of severity.

TABLE 1. Demographic Information of Patients (Categorized into Five Groups)

MAS level	Numbers of Patients	Sexes (Male/ Female)	Hand with Symptoms (Left/ Right)	Age (Years)
0	6	3/3	2/4	44.3 ± 18.4
1	15	11/5	7/8	62.7 ± 10.1
1+	3	3/0	2/1	56.0 ± 7.5
2	4	3/1	1/3	50.0 ± 9.5
3	2	2/0	2/0	38.7 ± 19.1

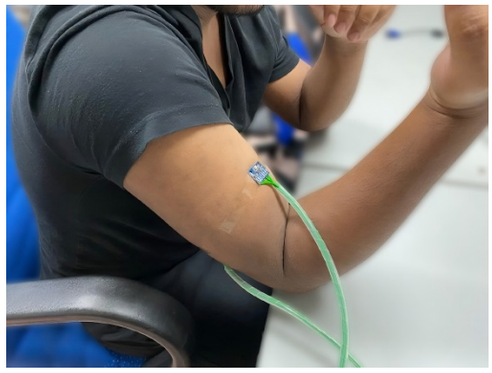
Quantitative Spasticity Assessment Technology (QSAT) is a platform designed to address inconsistencies in spasticity measurements by utilizing Mechanomyography (MMG) technology. This advanced system incorporates two principal sensors. The first sensor, an accelerometer Mechanomyography (ACC-MMG), is specifically designed to measure muscle vibrations in the biceps and triceps with a sensitivity range of ±2 g to ±16 g. For this study, the ±2 g range was selected to ensure optimal sensitivity in detecting minor muscle vibrations. The ACC-MMG sensor provides a 10-bit output, corresponding to $2^{10} = 1024$ distinct levels. Given that the output is signed, the range is symmetrically partitioned between positive and negative values, yielding 256 least significant bits (LSBs) per 1g of acceleration. The sensitivity of the ACC-MMG sensor, is critical for precise measurements, is expressed in Equation 1:

$$Sensitivity = \frac{2 \times 9.81\ m/s^2}{256} \quad (1)$$

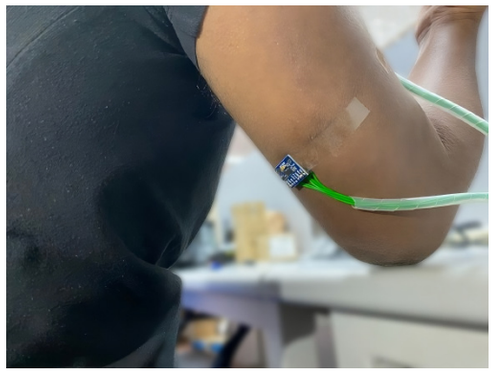
The second sensor in the system is a potentiometer, which accurately measures the angle of forearm movement during flexion and extension. The calibration process involved measuring the potentiometer‘s output voltage using a 16-bit Analog-to-Digital Converter (ADC) embedded in the microcontroller. With a reference voltage (V_{ref} = 5.0V), the ADC delivers a full-scale output. However, the mechanical limitations of the potentiometer‘s angular displacement restricted the voltage range to V_{min} = 0.000V and V_{max} = 1.628V. The angular position (θ) was calculated from the ADC-recorded voltage (V_{pot}) using the linear interpolation formula presented in Equation 2:

$$\theta = \frac{V_{pot} - V_{min}}{V_{max} - V_{min}} \times (\theta_{max} - \theta_{min}) + \theta_{min} \quad (2)$$

where θ_{min} = 0 degrees and θ_{max} = 135 degrees. This interpolation method ensured that the full range of the potentiometer‘s angular displacement was accurately reflected in the recorded data. As the potentiometer spins, its voltage output is transformed into a corresponding angular position based on the defined voltage-to-angle relationship. Additionally, the platform incorporates an elbow brace arm and a commercially available biological signal acquisition device (Raspberry Pi Pico) that captures both ACC-MMG and potentiometer data at a sample frequency of 166.7 Hz. This frequency was selected as it efficiently encompasses the muscle vibrational frequency range of 2 Hz to 100 Hz, providing effective detection of MMG signals while preventing aliasing (Ibitoye et al. 2014). The selection corresponds with the attributes of a dependable MMG transducer, encompassing high sensitivity in this frequency range, minimal susceptibility to random noise, ease of sensor attachment, biocompatibility, clinical appropriateness, and cost-effectiveness. Specifically, the tri-axial ACC-MMG accelerometer and potentiometer are integrated into the elbow brace and attached to the biceps and triceps muscle groups. This configuration facilitates simultaneous recording of single-channel potentiometer data and ACC-MMG signals across two channels. The ACC-MMG signals were recorded in three dimensions using accelerometers aligned along the x, y, and z axes. One channel serves to capture the data from the potentiometer, while two channels being specifically allocated for capturing the ACC-MMG signals. The three tri-axial accelerometers, oriented along the longitudinal, lateral, and transverse axes of the muscle fibers as illustrated in Figure 1, facilitate comprehensive recording of muscle activity.



(a)



(b)

FIGURE 1. Sensor Placement of the ACC-MMG: (a) Biceps and (b) Triceps

Prior to assessing muscle spasticity using the MMG platform, each patient‘s spasticity level was evaluated by a therapist utilising the traditional Modified Ashworth Scale (MAS) tool. The evaluation was carried out with the patient in a supine position, with their arms resting at their sides. The therapist performed passive movements and evaluated

spasticity levels by measuring the observable muscle resistance encountered during passive stretching. During the MAS assessment, ACC-MMG signals from the triceps and biceps muscles were captured, with sensors securely attached to the skin using transparent tape. Two channels of the ACC-MMG sensor were positioned on the muscle bellies of the biceps and triceps, respectively. The sensor was positioned with its x-axis parallel to the direction of muscle fibre contraction and its z-axis perpendicular to the skin surface. Additionally, a potentiometer was aligned with the elbow joint, integrated into the pivot of the elbow brace arm support. The QSAT experiment started with the therapist positioning one hand beneath the patient‘s lower arm in close proximity towards the wrist, whereas the other hand served to ensure stability of the forearm near the shoulder, as depicted in Figure 2. The patient‘s arm performed three cycles of passive range of motion, starting from a completely stretched position (0°) and advancing to complete flexion (135°), duration of each cycle being 2 seconds. All results were recorded and compiled in an Excel spreadsheet.

FIGURE 2. Configuration of QSAT Platform Measurements for Upper Limb

DATA PREPROCESSING

The data obtained throughout the experiments underwent to signal preprocessing utilising MATLAB R2023a software developed by MathWorks Inc. to ensure accuracy and reliability. Additional filtering was deemed unnecessary, as the initial preprocessing of the ACC-MMG and potentiometer data revealed minimal noise interference, which did not compromise the integrity of the signals. Consequently, the unprocessed data was used for subsequent analysis. The continuous data was segmented into distinct movement cycles by analyzing the elbow’s angular motion, which varies from 0° to 135° during flexion and from 135° to 0° during extension. The motion was continuously, devoid of any interruptions between flexion and extension. The potentiometer information, which monitored the angular position of the elbow, was utilized to precisely delineate the boundaries of each cycle. The beginning and end of each cycle were marked by critical points in the potentiometer signal, indicating when the elbow reached the initial point of the flexion phase (0°) and the final point of the extension phase (135°). This approach ensured consistent and accurate segmentation of the continuous movement data. The cycle segmentation was conducted by identifying changes in the potentiometer signal corresponding to transitions between the flexion and extension phases, thus ensuring that both phases were comprehensively captured and analysed without any disruption to the data stream.

FEATURE EXTRACTION AND SELECTION

The study obtained a total of 8 features, including Root Mean Square (RMS), Mean Average Value (MAV), Standard Deviation (SD), Peak to Peak Amplitude (PTP), Maximum (Max), Minimum (Min), Skewness (S), and Kurtosis (K). Time-domain features were obtained across the x_1, y_1, and z_1 axes for the biceps muscle and the x_2, y_2, and z_2 axes for the triceps muscle during the feature extraction phase. The axes represent the positions of the muscle fibers in relation to their longitudinal, lateral, and transverse allignments. Subsequently, the extracted features were compiled into a comprehensive dataset.

The Root Mean Square (RMS) quantifies the increase in amplitude of a signal and provides a dependable indicator of the level of muscle contractions or strain throughout the upper limb (Wang et al. 2017; Xie et al. 2020). The Mean Average Value (MAV) provides a numerical measurement of muscle strength and endurance, therefore reflecting the power and energy production of the muscle under evaluation (Rupsha Mukhopadhyay 2015). The variability of muscle activity was assessed by computing the Standard Deviation (SD) of the ACC-MMG signals along the x, y, and z axes.

Additionally, the Peak-to-Peak (PTP) value assesses the signal range by calculating the difference between its highest and lowest points of vibration amplitude over a given timeframe. This value quantifies the range of magnitudes of muscle oscillations or movements in through ACC-MMG signals. Moreover, the assessment of skewness and kurtosis has enhanced the comprehension of the distribution properties of muscle signals, in order to

facilitate a more detailed investigation of muscle activity and its variability. Collectively, these features provide a detailed representation of muscle activity, allowing for a thorough analysis of the relationship between MMG signal characteristics and muscle spasticity levels.

STATISTICAL ANALYSIS

A total collection of 90 datasets were obtained from 30 patients for the purpose of this study. Several statistical tests were utilized to examine the relationship between mechanomyography (MMG) signal features and muscle spasticity levels as assessed by the Modified Ashworth Scale (MAS). All statistical analyses were performed using SPSS version 27.0.1 (IBM Inc.).

To evaluate the relationship between the MMG signal features and the severity of muscular spasticity, a linear regression analysis was conducted. This statistical method establishes correlations between independent and dependent variables, with the regression model incorporating MMG features as independent variables and MAS levels as the dependent variable (Maulud & Abdulazeez 2020; Set Foong et al. n.d.). Key metrics such as the correlation coefficient (R), the coefficient of determination (R^2), and the *F*-test were used to evaluate the model. The correlation coefficient quantifies the strength and direction of the relationship, while R^2 indicates the proportion of variance in MAS levels explained by the MMG features. The *F*-test evaluates whether the regression model shows statistically significant.

In addition to linear regression, a Pearson correlation analysis was performed to assess the linear relationship between features of the MMG signal and MAS levels. The Pearson correlation coefficient (r) quantifies the strength and direction of the linear relationship between two continuous variables (Baak et al. 2020; Cui et al. 2020), helping to identify which MMG features are most strongly associated with muscle spasticity.

To further investigate the variations among MMG signal features across different degrees of MAS, a Multivariate Analysis of Variance (MANOVA) was employed. The inclusion of this statistical test was necessitated by the presence of multiple continuous dependent variables within the independent groups (Etana et al. 2024). MANOVA extends the ANOVA framework by simultaneously evaluating multiple dependent variables, thereby uncovering patterns that may not be evident when analyzing each variable individually (Aliff et al. 2024). This analysis determines whether the data has significant differences in MMG signal features between different levels of muscle spasticity.

RESULT AND DISCUSSION

STATISTICAL FINDINGS

The results of the linear regression analysis presented in Table 2, include essential metrics such as the correlation coefficient (R) and the coefficient of determination (R^2). The correlation coefficient (R) quantifies both the magnitude and direction of the linear relationship between the MMG signal features and MAS levels. The coefficient of determination, R^2, quantifies the amount of variance in the MAS levels that can be explained by the MMG signal features. The correlation coefficient value of 0.881 indicates a robust positive linear association between the MMG signal features and MAS levels, suggesting that higher values of MMG signal features are associated with higher MAS levels. This indicates that MMG signal features are reliable indicators of muscle spasticity. The coefficient of determination (R^2) quantifies the proportion of variance in MAS levels that can be explained by the MMG signal features. The R^2 value of 0.777 signifies that 77.7% of the variation in MAS levels can be explained by the MMG signal features incorporated in the regression model. The strong R^2 value demonstrates that the MMG signal characteristics significantly explain the variability in muscle spasticity measures. The number of predictors in the model has been taken into consideration by the adjusted R-squared value of 0.586, which is slightly lower than the R-squared value. This value continues reflects a substantial explanatory power of the MMG signal features in relation to MAS levels. Moreover, F-test statistic yielded a value of $F(41,48) = 4.076$, $p < 0.001$. This demonstrates that the regression model is statistically significant and provides a strong fit to the data, demonstrating that the MMG signal features have a significant influence on predicting MAS levels. These findings support the hypothesis that MMG signal can serve as an quantitative measure of muscle spasticity, complementing the subjective assessments typically used in clinical practice.

Pearson correlation analysis was conducted to evaluate the linear relationships between individual MMG signal features and MAS levels, with the results summarized in Table 3. The Pearson correlation coefficients indicate the magnitude and direction of the linear associations across each MMG signal features and MAS levels. Within the set of features, $Miny_1$ displayed the most robust negative correlation with MAS levels ($r = -0.542$, $p < 0.001$), demonstrating that lower $Miny_1$ values correspond to increased spasticity. In contrast, $RMSy_1$ had the strongest positive correlation ($r = 0.515$, $p < 0.001$), indicating that higher $RMSy_1$ levels are associated with greater severity of spasticity. Additional significant associations are

observed between $MAVy_1$ ($r = 0.425$, $p < 0.001$) and $Maxy_2$ ($r = 0.395$, $p < 0.001$), which also exhibit a positive correlation with MAS levels. Figures 3 and 4 illustrate the Pearson correlation scatter plots for Miny1 and RMSy1, respectively, in relation to MAS levels. The robust link evident in these figures highlights the importance of $Miny_1$ and $RMSy_1$ as essential factors for assessing spasticity. These findings verify the significance of these features in characterizing muscle movements and underscore their potential applicability in clinical settings, especially for objective spasticity assessments.

This study employed one-way MANOVA to detect and eliminate dependent and redundant features by a method of significant feature analysis. The technique was used to analyse the features and determine significant differences in mean values between the groups for each axis of the biceps (x_1, y_1, and z_1) and triceps (x_2, y_2, and z_2). A significance level of $p < 0.05$ was established as the threshold to reject the null hypothesis and identify significant variations among the dependent variables. There were no variations in the mean values between the groups, according to the null hypothesis for the MANOVA test. All the *p*-values for the features mentioned in Table 4, including $MAVx_1$, $MAVy_1$, $MAVz_1$, SDz_1, $PTPy_1$, $Maxx_1$, $Maxy_1$, $Maxz_1$, $Minx_1$, $Miny_1$, $Minz_1$, Sx_1, Ky_1, $RMSx_1$, $RMSy_1$, $RMSz_1$, $MAVy_2$, $MAVz_2$, SDz_2, $Maxy_2$, $Maxz_2$, $Miny_2$, $Minz_2$, $RMSy_2$, and $RMSz_2$, were below 0.05, leading to the effective rejection of the null hypothesis.

Moreover, this study distinguishes itself from comparable studies by prioritising time-domain MMG features, presenting a more straightforward and clinically adaptive methodology than the frequently utilised frequency-domain or multimodal analysis. This study performed one-way MANOVA, offering a more comprehensive multivariate analysis to uncover significant changes in MMG features across MAS levels, in contrast to past studies that employed methods such as Kruskal-Wallis tests or Spearman correlation. This study's independently MMG configuration exhibited practicality and adaptability for clinical use, facilitating deployment without sacrificing accuracy, in contrast to sophisticated systems that incorporate additional sensors or modalities. These contrasts highlight the study's contribution to enhancing spasticity assessment techniques, providing an objective, trustworthy, and accessible instrument that supplements subjective clinical evaluations.

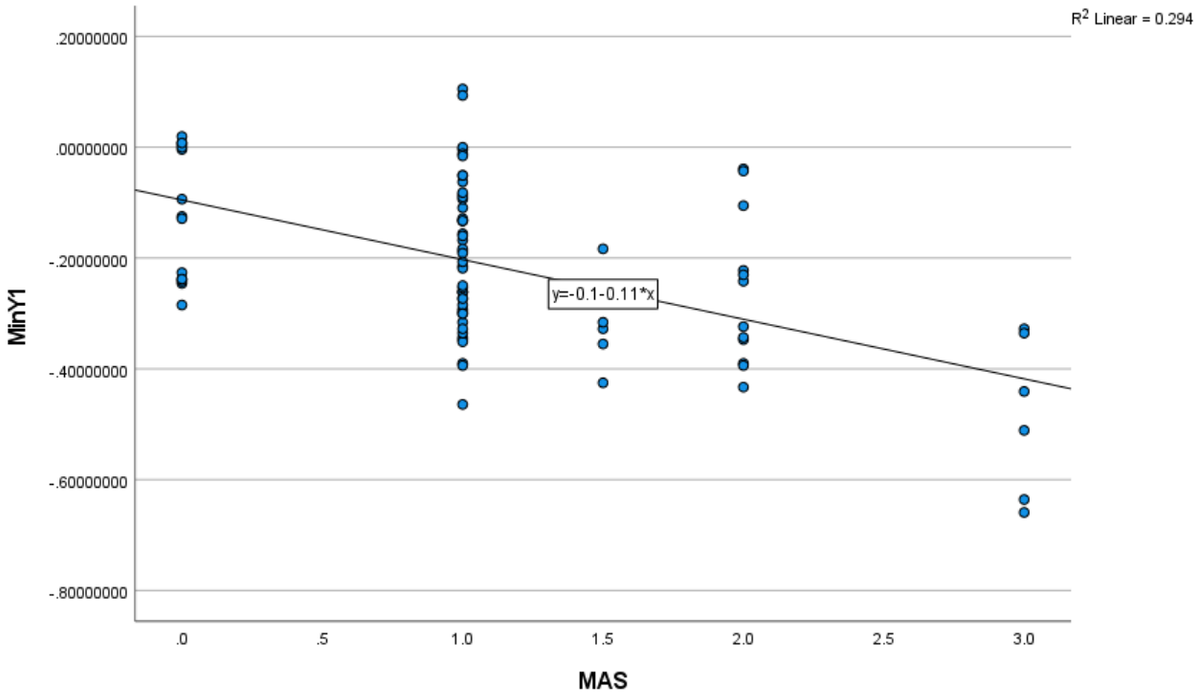


FIGURE 3. Scatter Plot of Pearson Correlation Between $Miny_1$ and MAS Levels

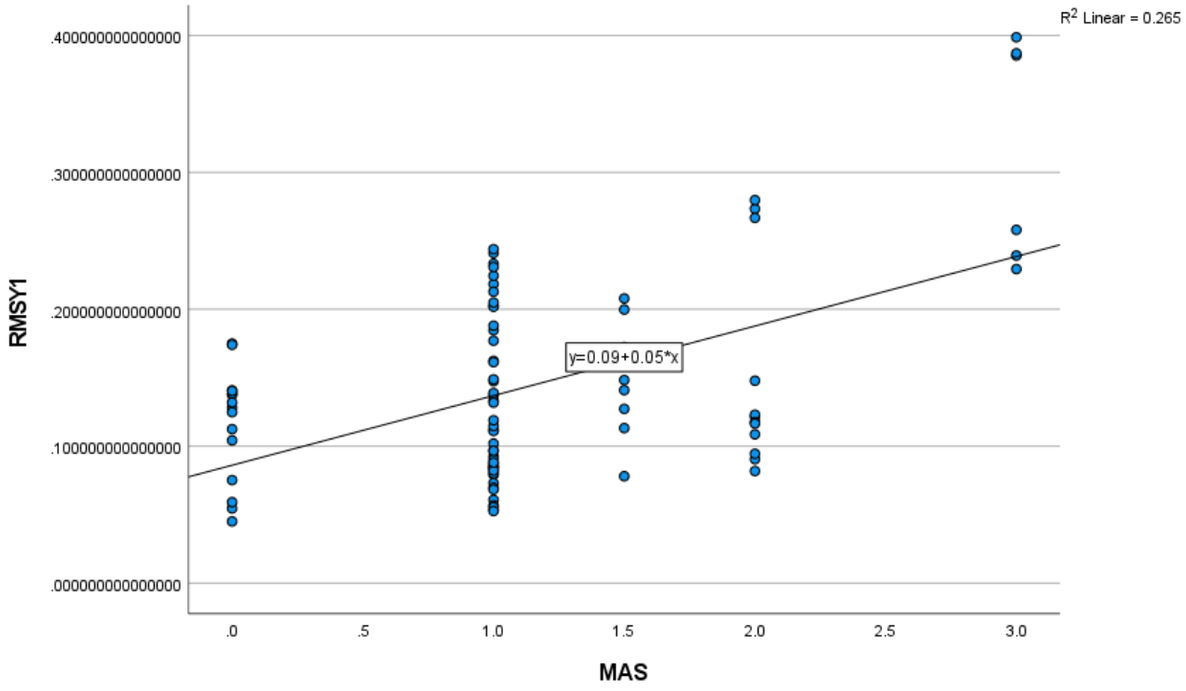


FIGURE 4. Scatter Plot of Pearson Correlation Between $RMSy_1$ and MAS Levels

TABLE 2. Linear Regression Analysis of MMG Features and MAS Levels

Model	R	R square	Adjusted R square	*F*	df	P values
1	0.881	0.777	0.586	4.076	41, 48	<0.001

TABLE 3. Pearson Correlation Coefficients Between MMG Features and MAS Levels

Features	Pearson Correlation (r)	P values
$MAVy_1$	0.425**	<0.001
$MAVz_1$	-0.279**	0.008
SDy_1	0.405**	<0.001
$PTPy_1$	0.326**	0.002
$Maxy_1$	-0.301**	0.004
$Miny_1$	-0.542**	<0.001
$Minz_1$	-0.228*	0.030
Sx_1	0.263*	0.012
$RMSy_1$	0.515**	<0.001
$RMSz_1$	-0.278**	0.008
$MAVy_2$	0.394**	<0.001
$MAVz_2$	-0.288**	0.006
SDy_2	0.226*	0.032
$Maxy_2$	0.395**	<0.001
$Maxz_2$	-0.282**	0.007
$Miny_2$	0.342**	<0.001
$Minz_2$	-0.284**	0.007

TABLE 4. One-way MANOVA Test Results for Differences in MMG Features Between Biceps and Triceps

Features	P Values					
	Biceps			Triceps		
	X_1	Y_1	Z_1	X_2	Y_2	Z_2
RMS	0.004	0.000	0.000	0.909	0.000	0.002
PTP	0.300	0.013	0.148	0.206	0.245	0.256
Max	0.000	0.003	0.000	0.708	0.000	0.011
Min	0.000	0.000	0.000	0.949	0.000	0.003
MAV	0.000	0.000	0.000	0.896	0.000	0.006
SD	0.583	0.001	0.157	0.335	0.282	0.042
S	0.001	0.939	0.311	0.345	0.946	0.065
K	0.213	0.020	0.309	0.221	0.456	0.557

CLINICAL IMPLICATIONS OF MMG IN ASSESSING MUSCLE SPASTICITY

This study's findings underscore the promise of Mechanomyography (MMG) as an objective and dependable technology for evaluating muscle spasticity, providing several significant clinical advantages. In contrast to the subjective Modified Ashworth Scale (MAS), MMG offers quantitative data that enhances the precision of spasticity evaluations. This objective assessment may diminish inter-rater variability and improve consistency in clinical evaluations.

The robust link between MMG features and MAS levels indicates that MMG may serve as a tool for monitoring the course of spasticity throughout time, facilitating the early identification of alterations in muscle tone. This is especially beneficial for patients in rehabilitation, as it enables more accurate modifications to therapy programs based on real-time data. The incorporation of MMG into wearable devices may provide continuous, at-home monitoring, providing patients and doctors with a cost-effective and non-invasive means of measuring spasticity beyond the clinical setting. This may enable prompt interventions and tailored treatment approaches, hence enhancing patient outcomes and rehabilitation efficacy.

CONCLUSION

Fundamentally, the primary aim of this study was to enhance the fairness and accuracy of spasticity assessments in patients with neurological disorders by evaluating the efficacy of Mechanomyography (MMG) signals in quantifying muscle spasticity. This study successfully demonstrated the ability of Mechanomyography (MMG) signal to provide an objective assessment of muscle spasticity through the implementation of appropriate statistical tests. To examine the relationship between MMG signal features and muscle spasticity levels measured by the Modified Ashworth Scale (MAS), statistical methods including linear regression, Pearson correlation, and one-way MANOVA were applied.

The linear regression analysis revealed a strong positive association between MMG signal characteristics and MAS levels, with a correlation coefficient (R) of 0.881 along with value of $F(41,48) = 4.076$, $p < 0.001$ and a coefficient of determination (R^2) of 0.777. These results underscore the significant explanatory power of MMG signal features in relation to muscle spasticity, indicating that MMG signal can reliably reflect the severity of spasticity as measured by MAS. Furthermore, the Pearson correlation analysis identified specific MMG signal features that are strongly associated with muscle spasticity. $Miny_1$ displayed the most robust negative correlation demonstrating that lower $Miny_1$ values correspond to increased spasticity while $RMSy_1$ had the strongest positive correlation indicating that higher $RMSy_1$ levels are associated with greater severity of spasticity. The use of Pearson correlation highlighting the potential of mentioned features as key indicators of spasticity levels. The one-way MANOVA test further validated the significance of these features, revealing notable differences in mean values across different MAS levels, which confirms their utility in distinguishing between varying degrees of spasticity. Overall, this study supports the hypothesis that MMG signal can serve as a robust, objective measurement of muscle spasticity, complementing clinical subjective assessments. Integrating MMG technology into clinical practice could improve the accuracy and consistency of spasticity evaluations, thereby facilitating more effective treatment planning and enhancing patient outcomes.

Despite these encouraging findings, this study possesses drawbacks that require consideration. The limited sample size and absence of MAS level 4 restrict the generalizability of the results. The investigation primarily utilized time-domain features, possibly missing significant signal properties. Future study needs to examine MMG signals in broader and more diverse patient populations and assess the integration of frequency-domain characteristics by increasing sampling rates to improve the sensitivity of spasticity assessments. The incorporation of robust machine learning algorithms has the potential to automate the classification of spasticity levels, facilitating more personalized treatment strategies. Successful clinical adoption of MMG necessitates the implementation of defined protocols and sufficient training for therapists to interpret MMG data proficiently. Confronting these obstacles will markedly enhance the accuracy and objectivity of spasticity evaluations, leading to improved patient outcomes and more effective rehabilitation approaches.

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DECLARATION OF COMPETING INTEREST

None.

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