

A Pilot Study for Assessing a Novel Method of Measuring Shoulder Activation in Healthy Volunteers Using Surface Electromyography

Sreten Franovic¹, Yang Zhou², Emily Lau³, Alexander D Pietroski¹, Noah A Kuhlmann¹, Vishwajeet Singh⁴, Chaoyang Chen², Stephanie J Muh^{1*}

¹Henry Ford Health System, USA

²Wayne State University, USA

³Wayne State University School of Medicine, USA

⁴Homerton University Hospital, London, UK

*Correspondence should be addressed to Stephanie J Muh; smuh1@hfhs.org

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Abstract

Background: Electromyography (EMG) technology has been shown to accurately measure individual muscle activation, force, and fatigue, and thus presents as an interesting aid to medical diagnosis. Surface EMG is a noninvasive alternative to traditional, intramuscular EMG. Our aim is to assess the feasibility of using surface EMG technology to measure activity of eight different shoulder muscles in healthy volunteers performing both daily living and range of motion exercises.

Methods: Nine subjects completed a series of three motions (abduction/adduction, internal/external rotation, and drinking). Eight surface EMG electrodes were used to measure muscle activity: anterior deltoid, middle deltoid, posterior deltoid, supraspinatus, infraspinatus, trapezius, teres major, and biceps brachii. Muscle activity was captured using wireless 3-dimensional Bluetooth sensors. ANOVA and principal component analysis (PCA) were used for statistical analysis to determine the pattern of shoulder muscle activation in response to upper arm's activity of daily life.

Results: ANOVA analysis showed significantly different root mean square (RMS) values among muscles for all three exercises ($p < 0.001$). Furthermore, for each individual muscle, there were statistically significant differences among the different motions ($p < 0.001$). PCA displayed significant correlations between muscles for each motion and predominant muscle groupings. ANOVA analysis showed significantly different peak frequency values among muscles for all three exercises, in each phase of the exercise ($p < 0.001$).

Conclusion: The results of this study indicate that kinematics of the muscles in the shoulder girdle and upper extremity can be accurately and effectively quantified using surface EMG. Specifically, force and fatigue can viably be measured and assessed in both superficial and deep muscles.

Introduction

Over the years, healthcare providers have used a host of physical examinations and clinical tools to assess a patient's physical functioning and health, but many of these assessment tools lack generalizability among physicians or the specificity and sensitivity to accurately diagnose a patient. Range of motion measures are one-way physicians assess many physical deficiencies in the upper

and lower extremity. These can be limited by discrepancies among testing methods or subjective interpretations of the findings, as some clinicians may have different definitions of range of motion deficits [1,2]. Further diagnostic tests may assess patient's pain in a variety of positions and motions, which continues to be limited by inter- and intra-rater reliability as well as each test's sensitivity and specificity [3-7]. Physicians may elect to use more specific tools, such as goniometers or dynamometers, to compare

exact degrees or force output levels of muscle groups, but these measures are still limited. The information gathered from these instruments is reflective of the ability of muscle groups to perform specific motions, rather than true health of the individual musculature responsible for the motion.

Electromyography (EMG) has emerged as an interesting aid toward medical intervention due to its ability to accurately measure individual muscle activation, force, and fatigue [8-11]. More specifically surface EMG (sEMG) presents as a noninvasive, yet still effective, alternative to traditional, intramuscular EMG – an invasive technique [12,13]. Although EMG analysis has long been used in both diagnostic and rehabilitative applications, in a variety of anatomical regions, methodology for collection, analysis, and application varies drastically throughout the literature and hinders its suitability for widespread use.

The shoulder is a particularly interesting site for EMG analysis due to the intricacies of deep and superficial muscle coordination in the shoulder girdle. Intramuscular EMG was previously preferred to sEMG when deep muscles were under analysis but recently some studies have suggested that sEMG could suffice as an accurate measure of multiple-muscle activation in the shoulder girdle [10,11]. While there is a general understanding in the literature that maximum voluntary contraction (MVC) provides the most standardized and reliable method of assessing musculature [14], there is a lack of agreement regarding how to effectively measure and analyze a host of shoulder muscle EMG profiles in patients that cannot perform maximum voluntary isometric contractions. Normalization of EMG profiles has been proposed in the past by dividing mean or peak values by their baseline counterparts, thus providing a relative increase in activation, although these studies have largely used

indwelling EMG on a small number of muscles or motions [15,16,17].

The purpose of this study was to assess the feasibility and validity of sEMG analysis on the upper extremity of healthy subjects in both daily living and clinical range of motion exercises. The secondary purpose of this study is to establish reference activation values and synergistic patterns for future clinical use in patients that cannot asymptotically elicit MVC.

We hypothesize that sEMG analysis, using baseline sEMG for the normalization of EMG measurement, will accurately differentiate metrics between a host of muscles in the shoulder girdle.

Methods

Institutional review board approval from the Wayne State University (IRB# 052619MP2E) was obtained prior to data collection or analysis. From December 2018 to May 2019, nine healthy individuals, aged 23.9 ± 1.13 years, were recruited to comprise the study group and underwent normative sEMG testing of shoulder muscle activity. They were informed of the experimental procedures and written consent was obtained. All subjects claimed to have no known current or previous upper extremity injuries.

Subjects completed a series of three motions (abduction/adduction, internal/external rotation, and drinking; Figures 1A-1C), which were separately grouped into three phases: resting, outward movements, and inward movements. Eight surface EMG electrodes were used to measure muscle activity: anterior deltoid (Channel 1, Ch1), middle deltoid (Ch2), posterior deltoid (Ch3), supraspinatus (Ch4), infraspinatus (Ch5), trapezius (Ch6),

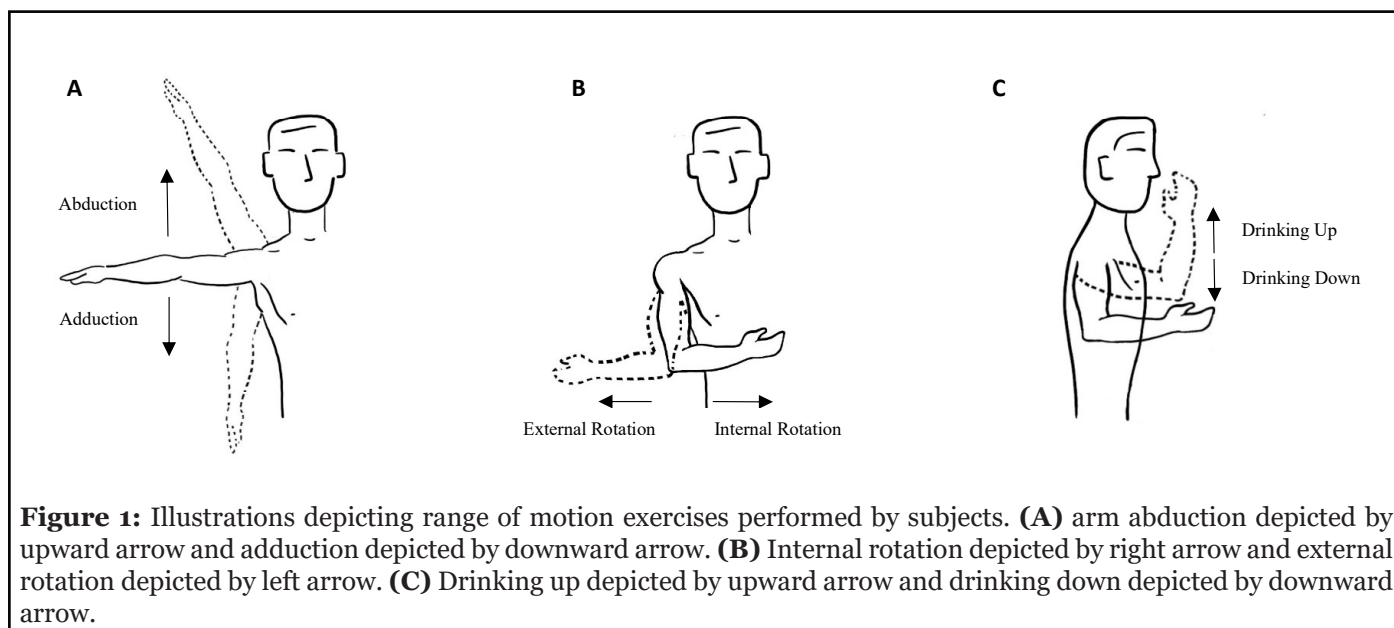


Figure 1: Illustrations depicting range of motion exercises performed by subjects. (A) arm abduction depicted by upward arrow and adduction depicted by downward arrow. (B) Internal rotation depicted by right arrow and external rotation depicted by left arrow. (C) Drinking up depicted by upward arrow and drinking down depicted by downward arrow.

teres major (Ch7), and biceps brachii (Ch8). Muscle activity was captured using wireless 3-dimensional Bluetooth sensors linked to a computerized analysis system (Model Trigno™ Avanti Platform, DELSYS Inc., Natick, MA, USA). Surface EMGs were placed on the central point of muscle belly in direction of muscle pull, after skin region was rubbed with alcohol.

In effort to standardize movements, the motions of participants were recorded via videotape and reviewed for consistency. Although any erratic movements were not included in EMG analysis, there was no reason to assume biased data as each subject completed each motion and speed three separate times. Raw EMG signals were band pass filtered using 3rd order Butterworth filter (20 – 350 Hz) and analysis was used to determine force and degree of activation (root mean square) and peak frequency of power spectral density (PSD) curves in each EMG signal using an EMG analysis software (EMG Works 4, DELSYS Inc., Natick, MA, USA). Exclusion criteria for this study was any previous indication of shoulder complication or intervention, or inability to perform any of the motions due to pain or stiffness.

Normalization of EMG measurement

In order to normalize EMG values among subjects for analysis, the proportion between the contraction phase RMS values and resting phase RMS values were calculated and assessed as percentage increases. In contrast, peak frequencies obtained from power spectral density curves were not normalized. This is due to the nature of a Fast Fourier Transformation (FFT) that provides a distribution of power as a function of frequency, which results in the analysis of the shape of the curve rather than the amplitude.

EMG data analysis

RMS values were taken from two locations: immediately preceding the motion (baseline) and during the entire length of the motion. RMS of the motion was then divided by the baseline RMS to determine percentage increase of RMS values from resting. Power spectral density (PSD) plots were created from each motions' EMG graph and peak frequency values were noted. Specifically, this PSD calculation uses the Welch method, where the data is first divided into overlapping sections with specified window length and overlap and then by the Hanning window type. The result is then zero-padded to specified FFT length. The magnitude squared of the FFT, of each of the sections, is then averaged to determine PSD.

Statistical analysis

One-way analysis of variance (ANOVA) was used to

identify any significant difference among muscle activation between movements and muscles. Least Significant Difference (LSD) post hoc test was used to determine specific differences between individual muscle activation. Principal component analysis (PCA) was utilized to uncover which factors (groups of muscles) were activated synchronously. Synergic activation of individual muscles was analyzed using PCA to determine synchronization of muscles in response to a specific arm motion. All analyses were performed using a significance level of 5%. SPSS software was used for all statistical analyses (IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.).

Results

The subject cohort included 6 men (66.7%) and 3 women (33.3%), aged 23.9 ± 1.13 years old (mean \pm SD). All available data was used for analysis.

Time domain (Root mean square)

The biceps brachii showed the greatest percent increase in RMS for the drinking up motion ($p < 0.005$), while the biceps brachii, anterior deltoid, and trapezius muscles showed the greatest percent increase for the drinking down motion ($p < 0.005$). The infraspinatus showed the greatest percent increase in RMS for abduction ($p < 0.005$), while the biceps brachii showed the greatest percent increase for adduction ($p > 0.05$). The anterior deltoid showed the greatest percent increase in RMS for external rotation ($p < 0.005$), while middle deltoid, anterior deltoid, and infraspinatus showed the greatest percent increase for internal rotation ($p < 0.005$). Average percent increases for each muscle, during each motion, can be seen in Table 1.

ANOVA analysis showed significantly different RMS values among muscles for all three exercises, in each phase of the exercise (resting, outward motion, inward motion) ($p < 0.001$). Furthermore, for each individual muscle, there were statistically significant differences among the different motions ($p < 0.001$, Table 1). Figures 2A-2C display the RMS progression of each muscle throughout the three phases of each motion.

Frequency domain (Power spectral density)

ANOVA analysis showed significantly different peak frequency values among muscles for all three exercises, in each phase of the exercise (resting, outward motion, inward motion) ($p < 0.001$). Each deltoid muscle as well as trapezius and teres major showed statistically different peak frequency values among the varying motions ($p < 0.05$). Average peak frequency values for each muscle, during each motion, can be seen in Table 2.

	Anterior Deltoid	Middle Deltoid	Posterior Deltoid	Supraspinatus	Infraspinatus	Trapezius	Teres Major	Biceps Brachii	ANOVA
Drink Up	164 ± 20	634 ± 117	122 ± 15	234 ± 26	538 ± 181	194 ± 35	102 ± 10	1269 ± 318	0.000
Drink Down	125 ± 12	267 ± 39	128 ± 16	119 ± 11	228 ± 62	143 ± 16	146 ± 27	309 ± 49	0.000
External Rotation	234 ± 77	109 ± 15	181 ± 42	349 ± 108	331 ± 134	629 ± 178	312 ± 56	175 ± 51	0.009
Internal Rotation	191 ± 48	122 ± 18	122 ± 25	292 ± 79	221 ± 56	438 ± 174	200 ± 63	507 ± 175	0.048
Abduction	2854 ± 401	5411 ± 767	1128 ± 307	1595 ± 539	3084 ± 1088	2026 ± 676	284 ± 56	881 ± 290	0.000
Adduction	1817 ± 360	2418 ± 365	703 ± 100	743 ± 197	2265 ± 1065	1301 ± 458	252 ± 38	753 ± 303	0.006
ANOVA	0.000	0.000	0.000	0.000	0.001	0.000	0.004	0.009	

All values are expressed as percentages (%) in the format Mean ± Standard Error.

Table 1: Analysis of root mean square percent increase by muscle sensor and motion.

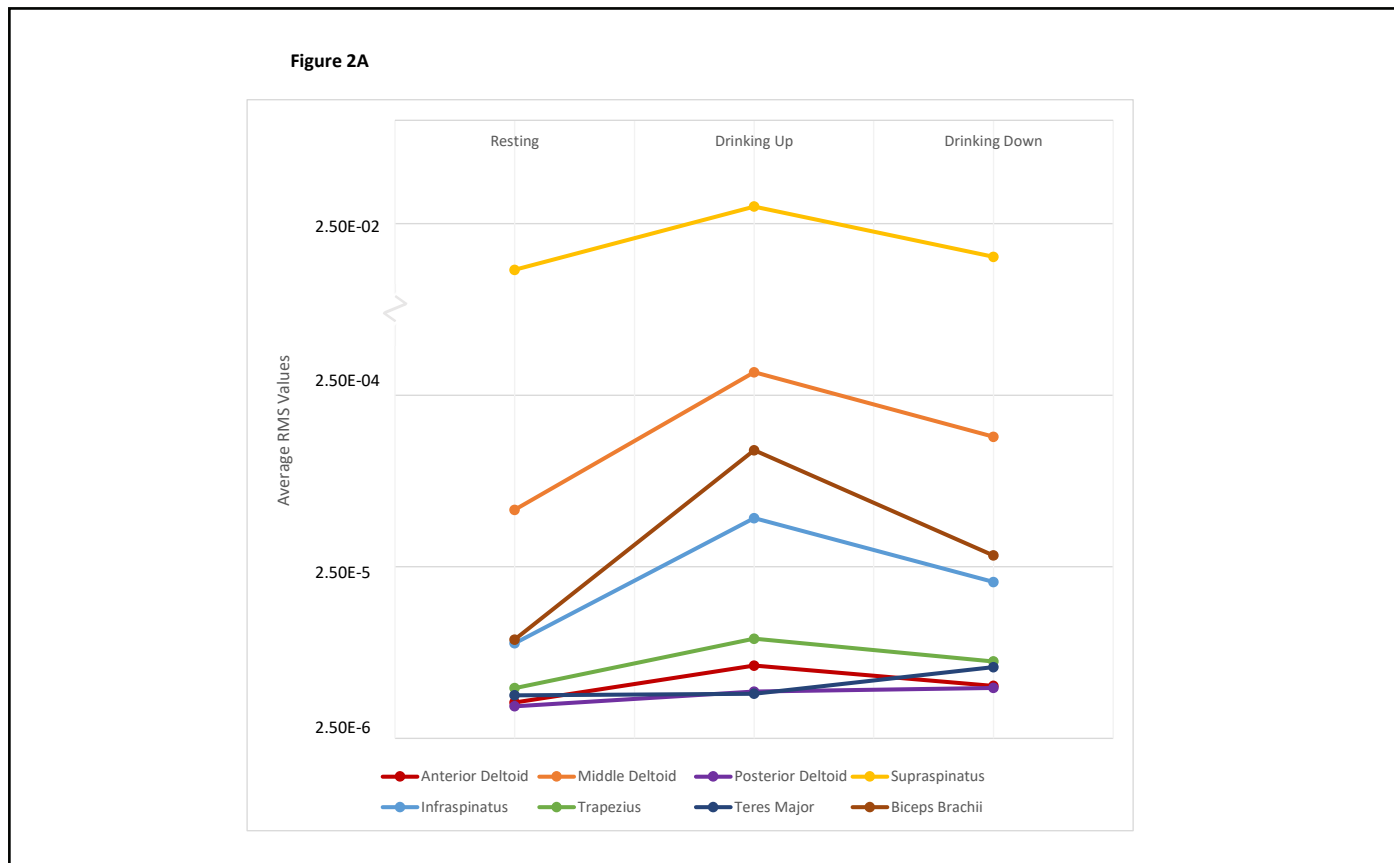


Figure 2B

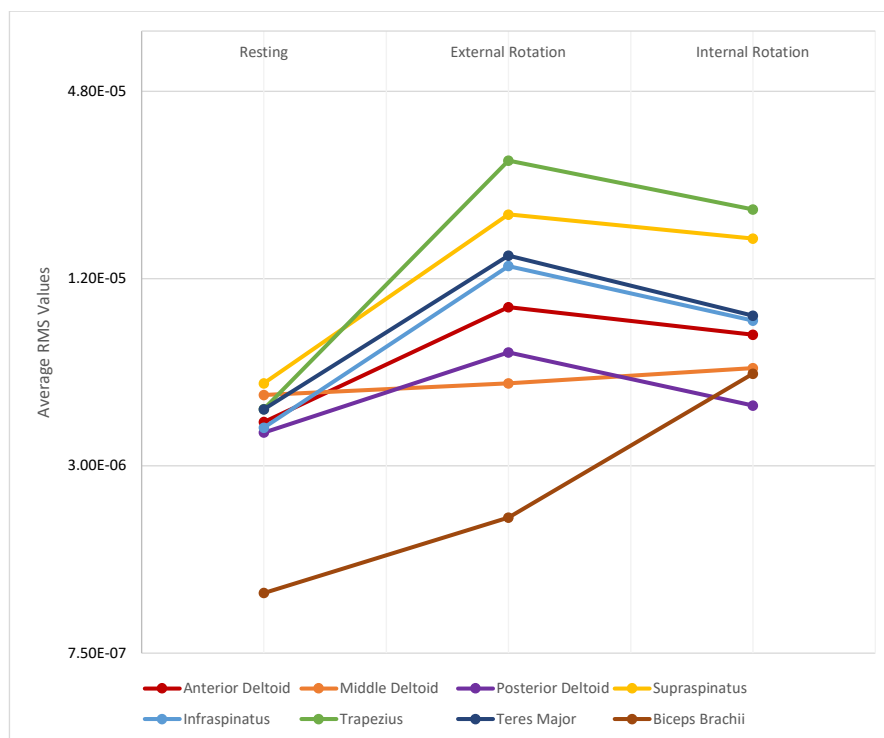


Figure 2C

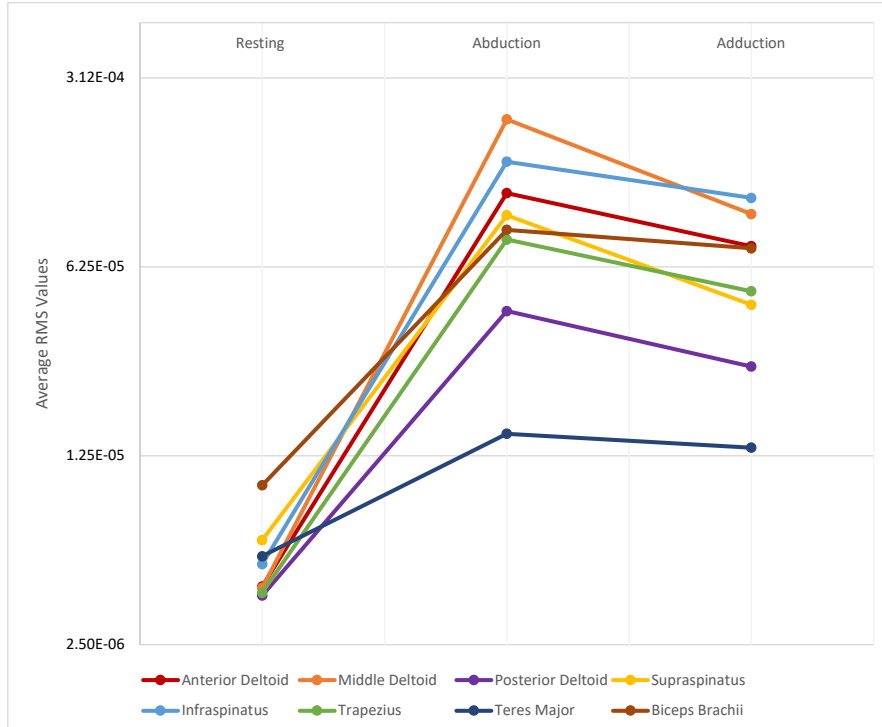


Figure 2: Graphical representation of average root mean square (RMS) values during motion progression. **(A)** RMS progression from resting to drinking up to drinking down. Note, break in Y-axis is present for reasonable graphical dimensions. **(B)** RMS progression from resting to external rotation to internal rotation. **(C)** RMS progression from resting to abduction to adduction.

	Anterior Deltoid	Middle Deltoid	Posterior Deltoid	Supraspinatus	Infraspinatus	Trapezius	Teres Major	Biceps Brachii	ANOVA
Drink Up	201.5 ± 25.7	131.9 ± 19.6	193.3 ± 19.4	198.2 ± 53.5	131.4 ± 9.1	163.5 ± 19.2	196.0 ± 21.9	111.2 ± 4.5	0.049
Drink Down	240.5 ± 26.6	117.7 ± 12.8	198.2 ± 16.5	199.8 ± 19.5	140.0 ± 13.6	180.8 ± 20.7	152.0 ± 18.1	124.9 ± 7.1	0.000
External Rotation	186.2 ± 31.5	148.9 ± 24.7	135.2 ± 21.4	166.2 ± 28.3	106.1 ± 11.3	96.7 ± 11.9	92.4 ± 11.0	99.3 ± 13.0	0.005
Internal Rotation	200.5 ± 31.7	178.2 ± 28.2	122.9 ± 20.3	173.1 ± 30.2	121.2 ± 17.1	127.2 ± 21.3	105.5 ± 14.9	91.5 ± 9.2	0.006
Abduction	101.9 ± 11.5	106.5 ± 10.7	102.0 ± 10.9	103.7 ± 15.2	135.2 ± 32.0	91.1 ± 10.3	96.4 ± 10.7	98.1 ± 76.2	0.647
Adduction	105.2 ± 11.7	102.6 ± 10.7	95.5 ± 10.3	105.3 ± 11.7	101.6 ± 11.3	95.6 ± 11.2	105.1 ± 14.9	107.2 ± 4.1	0.995
ANOVA	0.000	0.048	0.000	0.096	0.505	0.000	0.000	0.159	

All values are expressed as frequencies (Hz) in the format Mean ± Standard Error.

Table 2: Analysis of power spectral density peak frequency by muscle sensor and motion.

	Component 1		Component 2		Component 3	
	Muscle	R	Muscle	R	Muscle	R
Drink Up	Posterior Deltoid Supraspinatus Trapezius Teres Major Biceps Brachii	0.868 0.825 0.839 0.847 0.758	Middle Deltoid Anterior Deltoid	0.923 0.806		
Drink Down	Supraspinatus Trapezius Infraspinatus	0.899 0.810 0.892	Middle Deltoid Anterior Deltoid	0.896 0.774	Teres Major Biceps Brachii	0.800 0.808
External Rotation	Supraspinatus Trapezius Infraspinatus Teres Major	0.975 0.961 0.985 0.819	Posterior Deltoid Biceps Brachii	0.910 0.780		
Internal Rotation	Supraspinatus Trapezius Infraspinatus	0.783 0.939 0.959	Teres Major Biceps Brachii	0.714 0.947	Middle Deltoid Posterior Deltoid	0.947 0.863
Abduction	Middle Deltoid Anterior Deltoid Posterior Deltoid Supraspinatus Infraspinatus	0.878 0.832 0.845 0.831 0.843	Trapezius Biceps Brachii	0.831 0.636		
Adduction	Middle Deltoid Anterior Deltoid Posterior Deltoid Biceps Brachii	0.954 0.910 0.777 0.807	Supraspinatus Infraspinatus	0.915 0.886		

Table 3: Principal component analysis of root mean square per muscle and motion.

Factor analysis

Principal component analysis (PCA) revealed significant groupings of muscles that fired synchronously. Every motion displayed at least two distinct groups of synergic muscle activation, with both “Drink Down” and “Internal Rotation” displaying three distinct groupings. All muscle groupings and correlative factors can be seen in Table 3.

Discussion

The results of this study indicate that kinematics of the muscles in the shoulder girdle and upper extremity can be accurately and effectively quantified using surface EMG. Specifically, force and fatigue can be viably measured and assessed in both superficial and deep muscles. These assessments show feasibility in both daily living motions as well as widely-accepted range of motion exercises. Finally, we describe both reference values for healthy musculature activation and synergistic activation patterns. To our knowledge, no study to date has used normalization techniques of sEMG recordings to assess several shoulder muscles undergoing range of motion and daily living exercises.

Root mean square analysis has been investigated in a plethora of studies but has been at the center of controversy for its interpretation and application [15-20]. Many scientists believe that in order to standardize and generalize RMS measurements, we must measure them as a proportion of each individual patient’s maximal voluntary contraction, or MVC [18-20]. MVC has been widely accepted into the EMG community as an effective tool for comparing EMG measurements, but presents with issues when adapting to cohorts with traumatic injury or neurological dysfunction. For example, a patient that has recently undergone shoulder replacement, or has had a recent stroke, would reasonably not test near their actual maximal voluntary contraction. Thus, the present study extended previous efforts of EMG normalization without inclusion of MVC [15-17]. We found sEMG sensors to adequately capture EMG data, which was distinguishable by both individual muscle and motion, when normalization techniques were used. In this scenario, healthcare providers are better able to track patients progress during treatment.

Power spectral density analysis has also shown promise in the literature in its ability to demonstrate muscular fatigue over time [21,22]. Frequency shifts of spectral plots are indicators of muscular fatigue, specifically when these plots shift toward lower frequencies after muscular exertion [19]. Furthermore, some studies have shown that the percentage of area under the curve (AUC) that resides in lower frequency domains also correlates to muscular fatigue [23]. Our study demonstrates distinguishability of

several muscles in the shoulder girdle when PSD analysis is considered. Both area-under-the-curve and peak frequency were unique factors in each of the eight muscles tested. Our results suggest a positive outlook for the future of sEMG use in clinical settings.

Our study does present with notable limitations in design. Primarily, we offered no comparison to accuracy with indwelling EMG or advanced imaging systems. Thus, limiting our conclusion of validity in the clinical field, although previous studies have investigated and concluded significantly similar physiological measurements between indwelling and surface EMG [24,25]. Further validity studies may include comparison of MVC to non-MVC normalization, as well as indwelling EMG comparison. While lacking comparison, our study focused on the feasibility and ease-of-use in clinic and in accordance with a cost-effective view on healthcare. Furthermore, our study only included nine young adults thereby limiting our ability to analyze the data with demographic subgroup tests and thus limiting the generalizability of our reference values. While older patients may not exhibit the same RMS-normalized values, they can still be properly tracked using baseline normalization and their synergistic activation profiles should resemble those described in the present study.

Conclusion

By demonstrating the feasibility of using sEMG to accurately measure daily living and range of motion exercises in a host of upper extremity muscles, we have provided clinicians with a valid means of assessing patient muscular health. Thus, by identifying RMS and peak frequency values, as well as isolating synchronous firing patterns, we have described a muscular profile that can be referenced as a healthy standard or replicated for future use.

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