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Validity and Reliability of Strive™ Sense3 for Muscle Activity Monitoring During the Squat Exercise

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ABSTRACT

Background: Recent innovations in surface electromyographic (sEMG) technology have enabled the measurement of muscle activity using smart textiles. **Objective:** In this study, the Strive™ Sense3 performance monitoring system is evaluated against a research-grade system, Noraxon™, in measuring activity during the back squat exercise. **Method:** Seventeen participants performed three total trials of the squat exercise with a progressive load for individual trials equal to 30%, 60%, and 80% of their estimated maximum 1RM (one-repetition maximum). sEMG measurements from the rectus femoris were captured for the left and right leg by both systems. Pearson product-moment correlation coefficient (r) and intraclass correlation coefficient (ICC) values were computed for each trial to assess concurrent validity and interrater reliability of the Strive™ Sense3 device. Additionally, five coaches at the collegiate- and professional-level of Men's Basketball speak from an autoethnographic frame to the findings from this study. **Results:** Results ranged from "Poor" to "Excellent" validity and "Poor to Moderate" to "Excellent" reliability, with a majority of trials achieving "Good" or better results across all loads [93% trials: $r >= 0.7$; 87% trials: lower ICC 95% CI bound >= 0.75 (absolute sEMG); 98% trials: lower ICC 95% CI bound >= 0.75 (normalized sEMG)]. Higher validity and reliability for medium and heavy loads were observed in comparison to the light load, and several outliers indicate the need for coaches to lubricate sensors and ensure proper fit to collect accurate data. **Conclusion:** Examining results alongside practitioner feedback indicate the Strive™ Sense3 system is capable of tracking sEMG activity in comparison to a research-grade system.

Key words: Surface Electromyography, Wearable Electronic Devices, Reliability and Validity, Muscle Contraction, Correlation of Data

INTRODUCTION

The generalized aims of electromyography (EMG) are to analyze the function and coordination of muscles during different movements and activities, in different populations, under laboratory conditions as well as during activities of daily living (Clarys, 2000). Multiple systems exist for both surface and intramuscular EMG to assess muscle activation (Massó et al., 2010), each with their own advantages and disadvantages. Intramuscular EMG is generally used in clinical settings and is considered more precise, but since a needle electrode is required, it is invasive and sometimes painful to the wearer (Massó et al., 2010). Surface EMG (sEMG) requires more skin preparation and accurate positioning to avoid muscle cross-talk but has the advantage of being

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noninvasive and more appropriate for dynamic activities (Massó et al., 2010). Consequently, sEMG has become a popular solution for insights and evidence-based decisions in sport applications, such as detecting movement technique, abnormal muscle activation, evaluating injury risk, predicting performance as well as in recovery from injury and return to sport (Ball & Scurr, 2013; Clarys & Cabri, 1993; Lynn et al., 2018; Massó et al., 2010; Türker & Sözen, 2013; Vigotsky et al., 2018).

Research grade (RG) sEMG systems from companies such as Noraxon, Biopac, and Motion Lab Systems have become the gold-standard for measuring muscle activity (Desmarais & Giess, 2017; Lynn et al., 2018; Smith, 2019). However, these systems are often limited to a laboratory environment due to the additional hardware needed to amplify and perform computations on the signals. Conversely, wireless, wearable sEMG devices can aid in conveniently capturing muscle activity in various populations and in various scenarios, especially outside of a laboratory. Implementation of wearable body sensor networks has paved the way for much smaller, more feasible, less complex, and affordable sEMG systems (Lynn et al., 2018). Wireless sensors do have their limitations, such as sensor range, battery life, and continuous monitoring (Fong & Chan, 2010; Vigotsky et al., 2018). The advent of wearable technology and wearable EMG devices are successfully bridging these limitation gaps, but still require appropriate validation and refinement. In the field, coaches and practitioners have expressed a general distrust of certain types of novel wearable technology due to a lack of transparency in the representation of the data as well as an inconsistency in recording of values (Luczak et al., 2019). As such, further research and cross-validation of these novel wearable systems, especially in dynamic tasks, are warranted.

Novel types of wearable sEMG devices have been previously proposed (Jang et al., 2018; Lynn et al., 2018; Shafti et al., 2016; Smith, 2019) and some have been tested for validity and reliability during static isometric and dynamic activities against traditional RG systems (Desmarais & Giess, 2017; Finni et al., 2007; Lynn et al., 2018; Smith, 2019). Among the novel wearable sEMG systems specific to lower extremity athletic activities are the Myontec™ system (Finni et al., 2007), the Athos® wearable EMG system (Lynn et al., 2018), and the Strive Sense3™ system (Smith, 2019). These systems are incorporated into compression athletic shorts, predominantly analyzing lower extremity thigh muscles (Finni et al., 2007; Lynn et al., 2018; Smith, 2019). sEMG measurements collected from the quadriceps individually from the three vastii muscles and from the rectus femoris are commonly used to quantify performance in voluntary isometric contractions (Caterisano et al., 2002; Clarys & Cabri, 1993; Jang et al., 2018; Schwanbeck et al., 2009). Moreover, different types of squats such as the back squat, free weight squat, Smith machine squat, and wall sit squat have also been analyzed using sEMG recordings from the quadriceps group of muscles (Ebben & Jensen, 2002; Nishiwaki et al., 2006; Schwanbeck et al., 2009; Slater & Hart, 2017; Yuen et al., 2019). Additionally, sEMG was reported to be a reliable method for assessing reproducibility of muscle activation during controlled dynamic ballistic movements including jump landings and cutting (Fauth et al., 2010). Previous validity research in wearable sEMG shorts have measured muscle activity in the quadriceps during isometric and dynamic activities (Finni et al., 2007; Lynn et al., 2018; Smith, 2019).

Findings from studies of these systems as well as validation methodologies were mixed. Research on the Myontec™ system reported good agreement with traditional electrodes during knee extension in a seated position and was also found to be feasible to measure in real-time during a treadmill test (Finni et al., 2007). This solution has also been noted to be reliable during activities of daily living such as stair descent, stair ascent, and repeated unloaded squats (Bengs et al., 2017). One study of the Athos® system was reported to be consistent when compared against RG system Biopac over a range of dynamic activities, indicating good validity and reliability (Lynn et al., 2018). Another study concluded that the Athos® system was not consistent in its measurements and did not match up with the Noraxon™ system during dynamic activities such as bilateral hamstring curls and box step-ups (Desmarais & Giess, 2017). The only existing study of the Strive™ system was reported not to be a valid EMG acquisition system for dynamic activities (Smith, 2019). However, in both studies that concluded this form of sEMG was not valid, a major limitation was identified in that consistent care was not taken to properly lubricate the sEMG system prior to data collection (Desmarais & Giess, 2017; Smith, 2019). Additional limitations were identified in the study of the Strive™ system. The first limitation was that no formal analysis was conducted on dynamic activities recorded because "Sense3 did not acquire enough successful trials to do proper EMG analysis" and "the inability to record an acceptable EMG signal during the movement correlates to a fail if Sense3 were to be used in a real world, dynamic scenario" (Smith, 2019). This conclusion warrants further investigation as the author notes an inconsistency in the preparation of the surface electrodes:

> "Aside for the fitting of the shorts, Strive advised applying water to the electrodes before testing to optimize results. Applying water was not implemented until after the first couple of participants. This continued for a few participants, but then was aborted for the remaining participants. Nevertheless, a noticeable difference between results were not seen between the middle participants with the beginning and ending participants" (Smith, 2019).

This inconsistency indicates that the poor results were more likely due to poor contact that resulted from a lack of proper lubrication of sensors. Both studies that reported positive results of Athos® and Myontec™ speak specifically to the importance of the electrodes being wet when collecting measurements to ensure proper conduction (Finni et al., 2007; Lynn et al., 2018). Inconsistencies in results of the Strive Sense3™ system indicate the need for further investigation with proper implementation of an experiment. Moreover, a thorough literature review revealed there are no existing studies comparing traditional and textile-based sEMG system concurrently for the squat exercise over a progressive load. Therefore, the purpose of this study is to compare the Strive™ Sense3 wearable sEMG system against an RG sEMG system during the squat activity at different loads. From a practical standpoint, five coaches at the collegiate- and professional-level of Men's basketball speak to the findings from an autoethnographic frame based on previous experience using the Strive™ system in the field.

MATERIALS AND METHODS

Participants

Seventeen participants including twelve males (n=12, age=23.3±5.8y, mass=82.7±10.3kg, height=179.1±4.3cm) and five females (n=5, age=21.2±1.5, mass=58.3±3.0kg, height=160.5±6.6cm) were recruited for this study. Participants were screened via a pre-participation questionnaire to determine any physical contraindications to participation and exercise training history. The participants were recreationally trained and the inclusion criteria consisted of the following: (a) at least 18 years of age and (b) a resistance training history of three bouts per week for at least six months with at least two months of back squat experience and having no physical limitations to exercise. Participants were excluded if they had metabolic, cardiovascular, and or musculoskeletal conditions that would affect their performance. All participants signed an informed consent form prior to participation. The study was approved by the California State Polytechnic University, Pomona (CPP) Institutional Review Board.

Experimental Design

This was a within-subjects design study to validate the accuracy of the Strive™ Sense3 in capturing sEMG measurements during the back squat exercise with progressive loading. Participants were required to attend one testing session at the CPP Human Performance Laboratory. After eligibility was confirmed via questionnaire, participants underwent basic anthropometry measurements (height, weight, leg length and circumference). The participants were then asked to wear the Strive™ garment of an appropriate size. The embedded electrodes were to be in good contact with the skin on the rectus femoris of the quadriceps muscle. Then the leg opening of the Strive™ garment was folded to the bottom edge of the garment's embedded electrodes. The exposed skin directly below the bottom edge of the Strive electrodes was prepared for the sEMG electrodes of the criterion measure research grade (RG) device (Noraxon™ DTS EMG system). Afterwards, participants completed 10 minutes of treadmill walking or jogging followed by dynamic stretching. Then, participants performed the back squat protocol which began with a light warm-up using a self-selected load, which was 30% of their estimated one repetition maximum (RM). After three minutes of rest, participants performed the back squat using a load equal to 30% (light weight), 60% (medium weight), and 80% (heavy weight) of their estimated RM in the listed order. Each load was performed for 3 continuous repetitions and two minutes of rest was provided between each load. RG and Strive™ sEMG data were collected concurrently during each load trial and transmitted wirelessly to their corresponding data acquisition system for further analysis.

Procedures

Back squat protocol

The back squat protocol was executed using a standard squat rack, 20kg barbell, and Olympic weight plates (Rogue Fitness, Columbus, OH, USA). Selection for each load was based on a percentage of the participant's estimated 1RM (one-repetition maximum). Given the back squat experience, as confirmed during pre-screening, participants were confident in their estimation, and no issues pertaining to the absolute load were observed during any of the trials. During the back squat warm-up, feet placement was marked with tape to ensure replication across all three trials. Participants were instructed to perform each repetition with a constant tempo of 2s eccentric and 1s concentric phases. Tempo was aided using a metronome set at 60 beats per minute. Participants were instructed to refrain from performing extraneous contractions such as "squeezing" quadriceps at the end of the concentric phase, and participants completed the eccentric portion of the lift to 90 degrees of knee flexion. A physical blockade was positioned behind the participant to provide a landmark for the participant to stop the descent of the back squat. The height of the landmark was adjusted for each participant during the warm-up, and a goniometer was used to determine the landmark height in which 90 degree of knee flexion was achieved.

Surface electromyography

The sEMG measurements from the rectus femoris on both limbs were collected concurrently with Strive™ Sense3 and the Noraxon™ DTS EMG system, i.e. the RG system. The RG system captured sEMG amplitude data using bipolar adhesive sEMG electrodes (Noraxon™ Dual Electrodes, Ag-AGCL, spacing 2.0cm, Noraxon USA Inc., Scottsdale, AZ). The RG system used herein was utilized by multiple prior studies (Ebersole et al., 2006; Ekstrom et al., 2012) for assessing sEMG amplitude during exercise. Strive™ garments were fit to each participant such that the embedded electrodes of the wearable device were exactly positioned over the rectus femoris. The leg opening of the Strive garment was then folded such that the RG system electrode could be placed immediately below the Strive™ electrodes. For acquiring the sEMG measurements by the Strive™ system, there were no skin preparations at the site of contact as this is not a required procedure during practical settings; however, the electrodes were dampened with water to facilitate conductivity as end-users would do in real-world situations (via sweat). For data collection via the RG system, the electrode site was prepared directly beneath the bottom edge of the Strive™ electrode according to previous methods SENIAM (Hermens et al., 2000). The site was first shaved and then cleansed, abraded, and dried prior to RG electrode placement. The RG system sampled at a frequency of 1500 Hz while the Strive™ Sense3 acquired data at 21.33 Hz using a mobile device wirelessly interfaced to the garment and native software application developed by Strive™ for the Sense3 product. Although Strive™ Sense3 has the capability to acquire data at 1000 Hz frequency, in this study, the data was captured at 21.33 Hz for concordance with real-world cases in which end-users would monitor the data at this frequency for run time and efficiency purposes.

Data Preparation

Python™ was utilized to perform data preparation and data analysis. The first preparation step was to account for the different sampling rates from each EMG system. The Noraxon™ data were down sampled by the rate of 1500 / (21 + 1/3) meaning that, for every 70 samples acquired by the Noraxon™ system, only the measurement for the first sample was considered for the following analysis. The remaining 69 data points were discarded.

After matching the sampling rates, data from Strive™ and Noraxon™ were time-aligned such that any possible delays due to beginning data capture at different times between systems would be mitigated in the analysis. Data alignment was performed using time-lagged cross-correlation (Rhudy, 2014). The Strive™ data for each trial was lagged (shifted) repeatedly from the range of -200 to 200 samples for both the left and right limb. The correlation between the Noraxon™ and the shifted Strive™ data was calculated in each step to find the optimal amount of lag, n. Under the assumption that data collected for both limbs are already synchronized within its respective system, the best of the two correlations was used to align both limbs for each weight. Then, the original Strive™ data for both the left and the right limb was shifted by n samples to synchronize the Noraxon™ and Strive™ data (Figure 1) (Rhudy, 2014; Saucier et al., 2019).

After the preprocessing steps were completed, each trial was visually inspected to ensure proper alignment. If any trials were observed to not be properly aligned, the researchers revised the preprocessing approach accordingly. Consequently, the data collected for participants 3 and 14 were removed prior to analysis. For participant three, it was observed that the Strive™ sensor mounted on the right limb showed no response for most samples (i.e. sEMG amplitude=0 μV). For these trials, it is likely that this was a result of insufficient lubrication and consequently poor electrode contact with the skin, which has been observed in other studies analyzing sEMG embedded into clothing (Desmarais & Giess, 2017; Lynn et al., 2018; Smith, 2019). Due to this poor response, the data from Strive™ and Noraxon™ could not be properly aligned. After observing the measurements collected from participant 14, it was noted that the data from the right and left limb were switched. Therefore, to assure data accuracy, the measurements from participant 14 were also discarded. The plots of preprocessed data for all participants are presented in the Appendix.

Statistical Analysis

Validity

To assess concurrent criterion validity of Strive™ Sense3 in acquiring sEMG measurements, the Pearson's product-moment correlation coefficient value (r) was computed (Düking et al., 2018). Calculations for r can be seen in Equation 1, where x^i is the i^{th} Noraxon™ sample, y^i is the i^{th} Strive™ sample, and n is the sample size, or number of pairs of samples for a given trial (Mukaka, 2012). Pearson's correlation coefficient is a unitless value reported on the scale of -1 to 1, with a higher absolute value of the result indicating a stronger association between the two data sets. Correlation coefficient values were assessed in determining the association between the measurements of Strive™ and Noraxon™ electrodes for each trial with a specific weight (light, medium, or heavy) and specific limb (right or left) for each participant. Results were interpreted based on guidance suggested by Mukaka: 0.0 < r <= 0.3—no correlation; 0.3 < r <= 0.5—poor correlation; 0.5 < r <= 0.7—moderate correlation; 0.7 < r <= 0.9—good correlation; 0.9 < r <= 1.0—excellent correlation (Mukaka, 2012).

$$r = \frac{n(\sum x_i y_i) - (\sum x_i)(\sum y_i)}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}} \quad (1)$$

Reliability

To assess the interrater reliability of Strive™ in comparison to Noraxon™ when measuring muscle activity, the intraclass correlation coefficient (ICC) and 95% confidence intervals (CI) were computed for each trial. The ICC is reported as a value between 0 and 1, with results closer to 1 indicating a higher reliability (Koo & Li, 2016). When determining the quality of interrater reliability between the Strive™ and Noraxon™ measurement systems, ICC values are rated accordingly: 0.0 < r <= 0.5—poor reliability; 0.5 < r <= 0.75—moderate reliability; 0.75 < r <= 0.9 good reliability; 0.9 < r <= 1.0—excellent reliability (Koo & Li, 2016). Further, individual trials are rated based on their 95% CI, rather than the ICC value itself since this value is an estimate. Therefore, trials can be rated as "Good to Excellent reliability" if the CI spans multiple categories (Koo & Li, 2016). For example, in Figure 4, the "Poor to Moderate ICC" category in the stacked bar chart indicates a trial where the lower end of the 95% CI achieved a Poor rating (0-0.5 ICC), and the upper end of the 95%

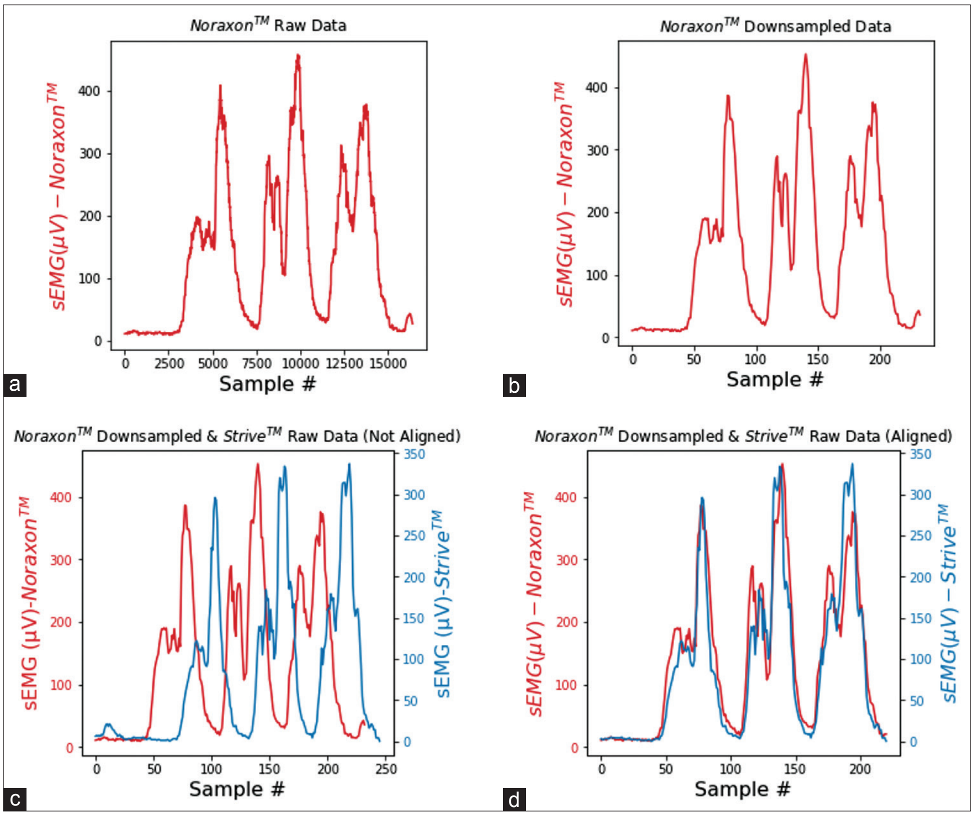

Figure 1. The preprocessing steps on a randomly selected trial corresponding to the measurements from participant 8, left leg with heavy weight. (a) Indicates original data from NoraxonTM, (b) Down-sampled data of NoraxonTM electrodes, (c) StriveTM and NoraxonTM data before cross-correlation, and (d) StriveTM and NoraxonTM data after cross-correlation

CI achieved a Moderate rating (0.5-0.75 ICC). Thus, the corresponding category encompasses both ICC ranges for the trial. In the case of the "Good ICC" category, both ends of the 95% CI were within the Good rating range (0.75-0.9 ICC), so only one range of ICC values are accounted for in this category. ICC values were calculated using Pingouin, a Python^{TM}-based statistical package (Vallat, 2018). Further, both absolute and normalized sEMG data have been analyzed.

A single-rating, consistency, two-way mixed-effects model was selected (Koo & Li, 2016). The formula for computing this form of the ICC model along with its respective Shrout and Fleiss Convention is denoted in Equation 2, where MS_R is mean square for rows (in this case, pairs of samples from both systems), MS_E mean square for error, and k is the number of measurements collected during a trial. For the Shrout and Fleiss Convention (*ICC* (3,1)), the number 3 indicates the model, while the number 1 indicates the model type (Koo & Li, 2016). A single rater type was used as the Noraxon^{TM} system is considered a research grade tool that functions as a baseline for the experiment, so the researchers are consequently not interested in the mean of the two rating systems. Consistency was chosen over absolute agreement since there was an inherent bias observed between the two systems during the preprocessing phase (i.e. Noraxon^{TM} output was generally higher than Strive^{TM} output). Lastly, the two-way mixed-effects model was selected since the two rating systems are the only systems of interest for this study (Koo & Li, 2016). Since there was an observed bias between the two systems for some trials, ICC analysis was performed for both normalized and absolute sEMG data. The data from both systems will be normalized based on the maximal voluntary contraction (MVC) of each trial.

$$ICC(3,1) = \frac{MS_R - MS_E}{MS_R + (K-1)MS_E} \tag{2}$$

RESULTS

Pearson correlation coefficient analysis produced results ranging from "Poor" correlation to "Excellent" correlation. ICC analysis of the 95% CI produced results ranging "Poor to Moderate" reliability to "Excellent" reliability. Normalizing the sEMG for both datasets improved the results to range from "Moderate" to "Excellent". The Strive^{TM} Sense3 device proved to be both valid and reliable for most participants (93% of trials with "Good" correlation or higher; 87% of absolute sEMG trials with "Good" reliability or higher, 98% of normalized sEMG trials with "Good" reliability or higher). Figure 2 depicts the range of *r* values across each weight-limb combination, summarizing all participants included in analysis. Figures 3 illustrates the mean and standard deviations of the estimated ICC values across all weight-limb combinations, while Figure 4 demonstrates a distribution of each trial's 95% ICC CI for all weight-limb combinations.

Validity

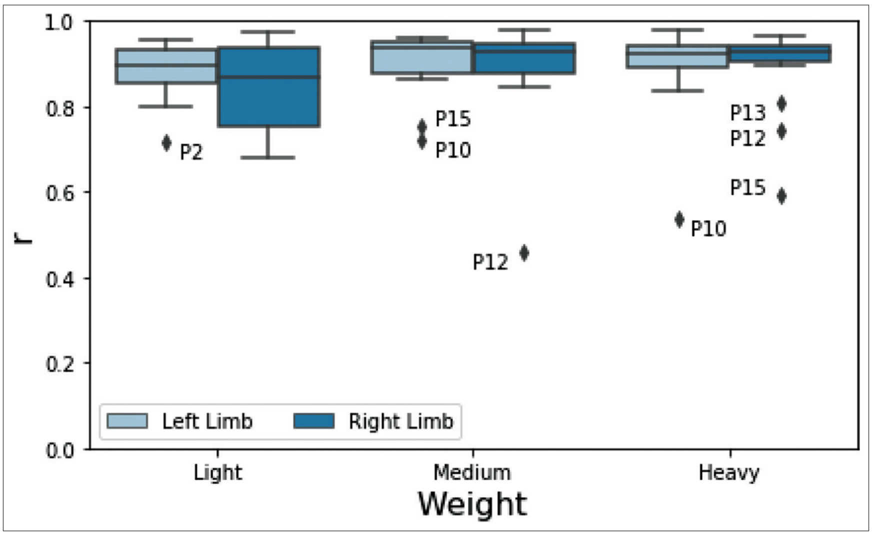

Figure 2. Boxplots of range of Pearson correlation coefficient (*r*) among weight and limb across all trials. Outlier trials are denoted by participant

Reliability

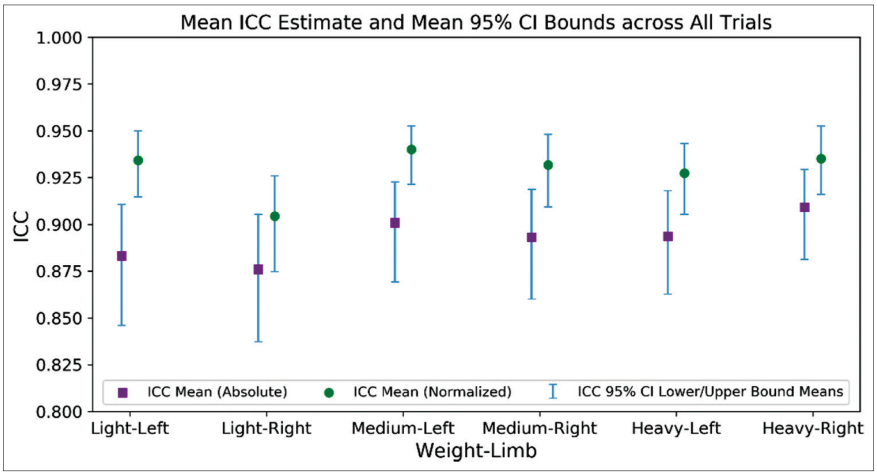

Figure 3. Mean ICC estimate, 95% CI lower and upper bounds for all trials measuring absolute and normalized sEMG. Note: Visualization is constricted to ICC >= 0.8 to depict relative differences between limb segments and weight amounts

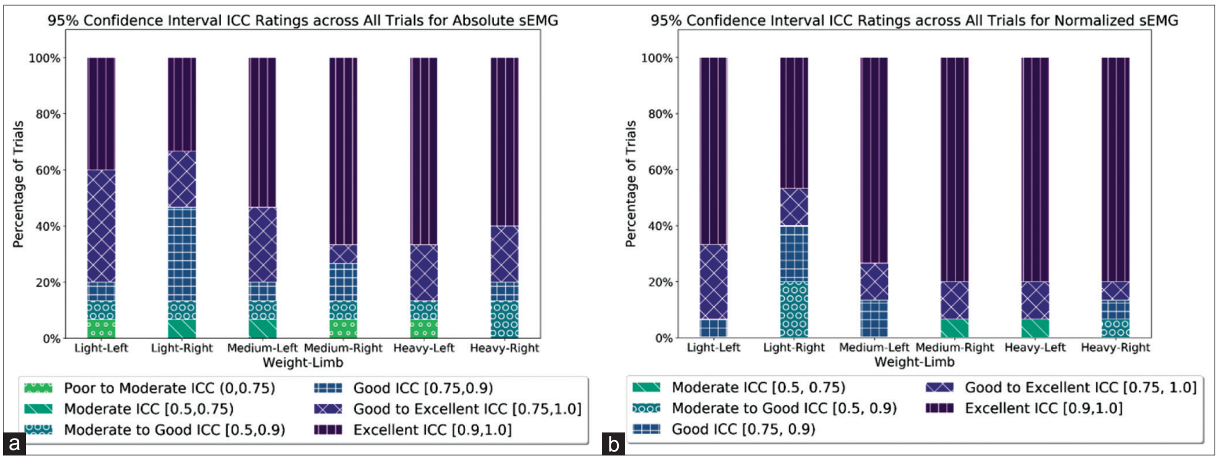

Figure 4. Stacked bar chart representing proportions of trials falling within certain ICC ratings based on upper and lower bounds of 95% CI when measuring (a) absolute sEMG data and (b) normalized sEMG data. Categories including ratings such as "Poor to Moderate" indicate CI spanned across multiple ICC ratings

DISCUSSION

Pearson Correlation Coefficient (r) Analysis—Validity

Strive™ measurements revealed a great capability in explaining the variation among the Noraxon™ measurements evaluated by the *r* measurement. When observing individual trials, *r* values ranged from poor to excellent correlation. For the one trial that resulted in "Poor" correlation, it was apparent that there was poor contact between the sensor and the muscle, which was likely a result of insufficient lubrication of the sensor (Lynn et al., 2018; Smith, 2019). Pearson correlation coefficient values for participants averaged across all six weight-limb combinations showed an average $r > 0.7$, indicating good correlation among all participants. The overall mean *r* was equal to 0.883 when accounting for all trials across all participants, indicating good correlation overall between the Strive™ and RG sEMG data. There is little to compare to other literature as similar studies did not collect measurements from two systems concurrently (Desmarais & Giess, 2017; Smith, 2019) and only compared peak, 95th percentile, and sum values rather than values collected over an entire movement (Lynn et al., 2018; Smith, 2019). Mean *r* values were lower for both limbs when participants squatted with the light weight in comparison to the medium and heavy weights. This could indicate that the Strive™ sensors more accurately measure muscle activity when the participant's squat load is greater. Though this study is the first of its kind in comparing two forms of sEMG concurrently over a progressive load during the squat exercise, previous research indicates that overall sEMG output increases with higher loads, consequentially supporting the notion that there is a greater amount of muscle activity to detect at higher loads (Alkner et al., 2000).

Intraclass Correlation Coefficient (ICC) Analysis—Reliability

When observing trials among weight and limb for the absolute sEMG data, at least 80% of trials were categorized as "Good" or higher for all weight-limb combinations (see Figure 4a). Trials categorized as "Excellent" occurred more often for the medium and heavy weight trials, further suggesting the notion that sEMG muscle detection is more reliable in the presence of more muscle activity. Trials with ICC CIs categorized as "Moderate" or worse occurred for participants 1, 10, and 12. Normalizing the sEMG data from both systems improved the results overall, with the worst-case trial reliability still being categorized as "Moderate" (see Figure 4b). Mean ICC values increased by roughly 0.02-0.07 for all weight-limb combinations after normalizing the data, which indicates that the Strive™ system is more consistent in measuring muscle activity in comparison to the RG system when analysing a percentage change of output rather than a change in the raw data. Previous literature has found success with this and elected to perform analysis with normalized sEMG data instead (Lynn et al., 2018). Besides the light weight, right limb combination, all other weight-limb combinations achieved ICCs of "Good" or better for 90% of trials after normalization. This discrepancy in performance could have been a result of displacement of the sensor in the right leg in which it was unable to accurately detect muscle activity until a certain muscle intensity was reached (Massó et al., 2010). Four percent of trials resulted in poor correlation, which is likely either due to poor contact with the sensor or improper fit of the shorts to the participant. This can be expected as other studies have noted poor participant data due to poor contact with the skin (Desmarais & Giess, 2017; Lynn et al., 2018; Saucier et al., 2019). For the purposes of this study, the researchers elected to keep these results in the overall calculations as these issues will still be prevalent in a real-world setting and need to be factored in when performing analysis of sEMG data.

Application for Coaching Practitioners

Often in the validation of newer technology, the perspective of the practitioner is most critical as they are the frequent users of the solution. The last five authors of this study are coaches at the collegiate- and professional-level of Men's Basketball and will use an autoethnographic frame to speak as practitioners to the research findings, Strive™ Sense3 technology, and human performance data collected from wearables (Brown et al., 2020; Luczak, Burch V, Smith, Lamberth, & Carruth, 2020; Luczak, Burch V, Smith, Lamberth, Carruth, et al., 2020; Luczak, Burch, et al., 2020; Shelly et al., 2020). The goal for any strength and conditioning coach (S&CC) working with elite-level athletes is to design a program regimen that best compliments and builds upon their existing skills and strengths while minimizing weaknesses and mitigating injuries. Coaches at this level should be experts in both their craft and the science behind human performance. Wearable solutions such as Strive combined with expertise from data scientists will likely never replace the S&CC as good coaches understand the context of the training and the uniqueness of how each of their athletes are built and perform. Wearables and the data they produce are instead additional tools used to aid the practitioner in making decisions about health and safety. Wearables are only as useful as the added value their data provides and if said data is consistent. The practitioner authors agree that "consistently inaccurate data is at least actionable while inconsistently accurate data is garbage." The point being that with consistent data, it does not have to be perfect to show changes in performance output. Vast changes in data depicting day-to-day performance may not explain what issues exist or what caused the change, but they provide a red flag indicator that the S&CCs should investigate as the change in output may indicate a problem. Given this overly simplified explanation of the relationship between practitioners and their wearables tools, the importance of validating the true capability for accurate data collection from a human performance-based technology is made clear. Therefore, validating a new tool against a proven and previously validated technology is a critical step in trust, something often missing from technologies in the wearable space (Luczak et al., 2018, 2020).

While further validation is always recommended and will be conducted by this research team, the results of this study presently demonstrate that the Strive™ Sense3 can be a valid and reliable device for measuring sEMG responses without the challenges of expecting student- or professional-athletes to conduct training movements within the confines of a laboratory and at the expense of keeping sEMG electrodes attached. The intent of the Strive™ Sense3 is to capture both external loads (how much movement and intensity of movement) as well as internal loads (muscle activation) over the course of a workout or competition. The author practitioners understand that while external load across many of the athletes performing the same workout regimen may have similar totals, the internal load total may vary indicating that some athletes are more efficient in their movements and muscle activations than others (Petway et al., 2020). Therefore, given these results, Strive™ Sense3 can aid S&CCs and other training practitioners in terms of (letters are unnecessary) load management, neuromuscular fatigue monitoring, baseline movement signature through various stationary and dynamic movements, capturing information on specific muscle contraction patterns, return to play protocols for injured athletes, and successful organization and execution of a periodized approach to load management with elite athletes. Author practitioners on this paper have successfully used Strive™ Sense3 during return-to-play protocols. Strive™ has been used to identify and immediately address any asymmetries being developed during athlete rehabilitation. The data generated by Strive™ ensures S&CCs that they are progressing in their training program appropriately while providing a visual "peace of mind" to the athletes who see their improvements visualized in the performance reporting. Not every athlete responds to stress in the same way, but using Strive™ to collect internal and external loads while also understanding the context of the data by knowing each athlete individually enables S&CCs to ensure training is optimal for all members of the team. Further, Strive™ and similarly validated wearable technology empowers S&CCs to objectively measure key performance indicators, or KPI's, and overlap them with more subjective data from wellness questionnaires such as RPE (rate-perceived exertion), sleep quality, daily readiness, and overall physical preparedness.

While practitioners express the benefits of using the Strive™ Sense3 and similarly validated wearables common to the collegiate and professional ranks (Luczak et al., 2020), there are areas for opportunity as with any new technology. While S&CCs generally have educational and training backgrounds in kinesiology areas such as biomechanics and physiology, the head coaches and positional coaches may not. The visual data presentation could be easier for all stakeholders to understand as head coaches want the most pertinent and exception-based information to be quickly digestible. Other challenges when working with Strive™ are common to many wearables and this includes inventory management and charging. Industrial companies had to combat the problem of large amounts of technology years ago and thus created equipment issue rooms and staff to manage technology (Burch et al., 2019).

Additional challenges specific to Strive™ that practitioners pursuing the use of this technology should be made aware is the need to keep the sensor pads lubricated as this is often required to record data. The practitioner authors stress the importance of wetting the pads prior to use, otherwise data capture will be inconsistent at best. Once athletes begin to sweat, the pads remain moist and data collection is consistent but prior to sweat activation, little to no data may be recorded. This issue exists in laboratory EMG systems and was experienced over the course of this study specifically in outlier participants. This problem has also been experienced by authors of this article such that wetting the pads before use is now part of their equipment management strategy prior to every practice or competition.

Lastly and from a recruiting and scouting perspective, professional scouts typically do not utilize data from wearables such as Strive™ to make assessments about which players to observe or consider for the draft. They do, however, often rely on the expertise of the S&CCs at the collegiate level to understand if the physical capabilities of the athlete align with the expectation of playing at the most elite levels of the game. All aspects of the player are important in the evaluation process for promoting a collegiate level athlete to the professional leagues. Professional scouts ask questions of S&CCs and athletic trainers that would be more general in nature. But the answers provided by S&CCs can be more informed if they are using technologies like Strive™ to baseline athletes and manage their workloads. Further, in the draft evaluation process, the members of a professional organization who would most benefit from the specific data provided by Strive™ are the S&CCs and athletic trainer that could inherit the athletes, their capabilities, and their past injuries if they are drafted. The use of wearables and additional data allow scouts and their colleagues to understand the projected physical trainability and how much better athletically the prospect can become.

Limitations

Investigating the data more precisely indicated that there are some outliers corresponding to data from participants 2, 10, 12, 13, and 15 (see Figure 2). When investigating the outlier data, the researchers point towards two potential reasons for poor results in the data: (a) the Strive™ sensor was not sufficiently lubricated prior to data collection, and therefore made poor contact with the rectus femoris during the trial, and (b) the Strive™ shorts themselves were not an ideal fit for the participant, and was consequently not placed optimally thereby failing to pick up more subtle changes in muscle activity. The data observed in the right limb for participant 12 supports the first case. In Figure 5, there was poor contact between the Strive™ electrodes and the rectus femoris on the right limb, thus resulting in data points where the amplitude would sporadically drop, sometimes to 0 μV. Existing studies seeking to validate sEMG-based athletic shorts have reported similar instances of poor contact with the skin due to lack of lubrication (Desmarais & Giess, 2017; Lynn et al., 2018; Smith, 2019). This same behaviour can be seen for participant 3 in the Appendix section, except much worse. Since there was a significant lack of meaningful data for participant 3 in the medium and heavy weight trials, the researchers excluded this data from the analysis as it was not clear whether the data was being properly aligned in the cross-correlation preprocessing phase (Lynn et al., 2018; Smith, 2019).

In the second case, trial data from participant 2 indicated that the shorts may not have fit the participant well, and thus the output in the Strive™ sensors did not pick up as much of the subtle changes in muscle activity as the Noraxon™ sensors. Figures 7a and 7b show an example where relative peak values did not much up well between both systems. Figure 7 shows examples where the shorts simply did not seem to fit the participant well and did not trend accurately with the Noraxon™ data. This ultimately led to the outlier results that were discovered during the analysis phase of the study. For Figure 8b, it appears that the subtle changes in peak data were not tracked as accurately with the Strive™ system, like the data shown in Figure 6 for participants 1 and 2. In Figure 7a, the Strive™ sensor detected initial mus-cle activation as participant 10 began the squat but did not continue to detect the muscle activity as the participant com-pleted the execution of the squat. Suggestions from other studies indicate that proper fit of sEMG-embedded athletic wear is an important factor to consider for accurately collect-ing data (Aquino & Roper, 2018; Smith, 2019). For the poor results in Figure 7c, it appears that a combination of poor fit of the Strive™ shorts and insufficient lubrication of the elec-trodes occurred during this trial. Figure 7d presents a single edge case that was discovered where the Noraxon™ system seemed to spike randomly during the trial, which could have been a result of poor contact or random noise during the squat. This was the only trial of the sort for participant 6, which could be a potential reason for the light weight, right limb summary results being noticeably worse than the other weight-limb combinations.

A key takeaway from examining these outliers is that care must be taken to properly lubricate the Strive™ electrodes prior to use. This is typically caused by the wearer's sweat but for testing and validation activities, or any activities prior to sweat forming, contact between the sensor and the wearer may be poor thereby resulting in inconsistent data (Lynn et al., 2018; Smith, 2019). This issue may be mitigated when the athlete remains active and generates enough sweat to assist with lubrication of the sensor. Further, when collecting data with the Strive™ shorts, it is imperative that the shorts be properly fitted to the athlete and that the sensors are precisely positioned on the muscles (Aquino & Roper, 2018; Smith, 2019). A final consideration to note is the overall improvement in validity and reliability in trials where participants lifted medium and heavy weight. This trend could indicate that the Strive™ shorts function better during more intense muscle activity. Though existing literature has not validated sEMG athletic shorts against a progressive load, previous research on the squat exercise indicates that muscle activation increases with barbell weight (Clark et al., 2012; McCaw & Melrose, 1999; van den Tillaar et al., 2019). Consequently, the technology may perform more optimally for activities that require greater muscle activity such as powerlifting and football, whereas cardio-intensive activities such as running and basketball

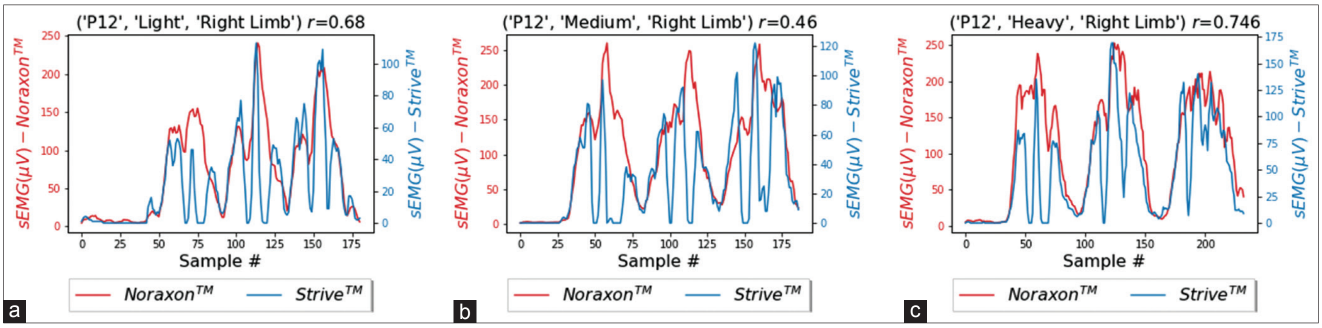

Figure 5. Data corresponding to participant 12 (P12) exhibiting drops in StriveTM sEMG amplitude in the right limb: (a) data from right limb on light weight trial, (b) data from right limb on medium weight trial, and (c) data from right limb on heavy weight trial.

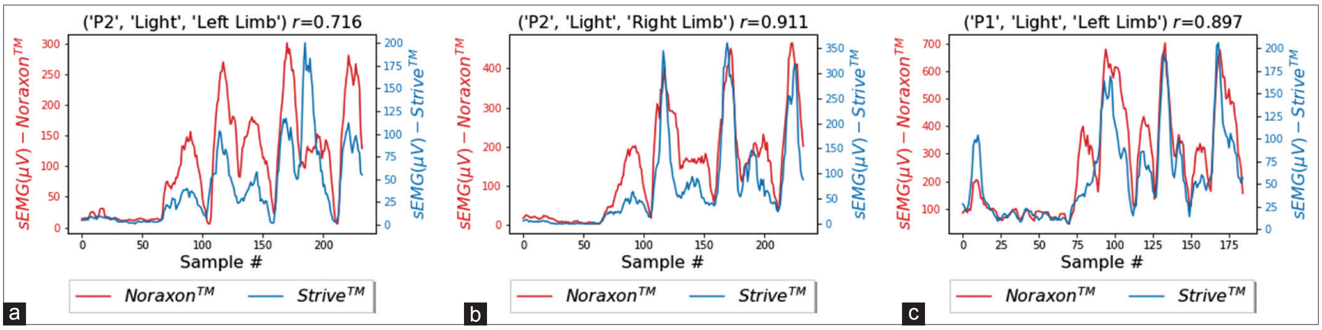

Figure 6. Outlier data for participants 1 and 2 (P1, P2) where subtle changes in NoraxonTM were not tracked accurately by StriveTM. (a) Data from the left limb during the light weight trial (P2), (b) Data from the right limb during the light weight trial (P2), and (c) Data from the left limb during the light weight trial (P1). In this case, the StriveTM sensor on the left limb may not have been placed well or differences in participant anthropometries or leg symmetries caused the participant leg not to properly align with the sensor.

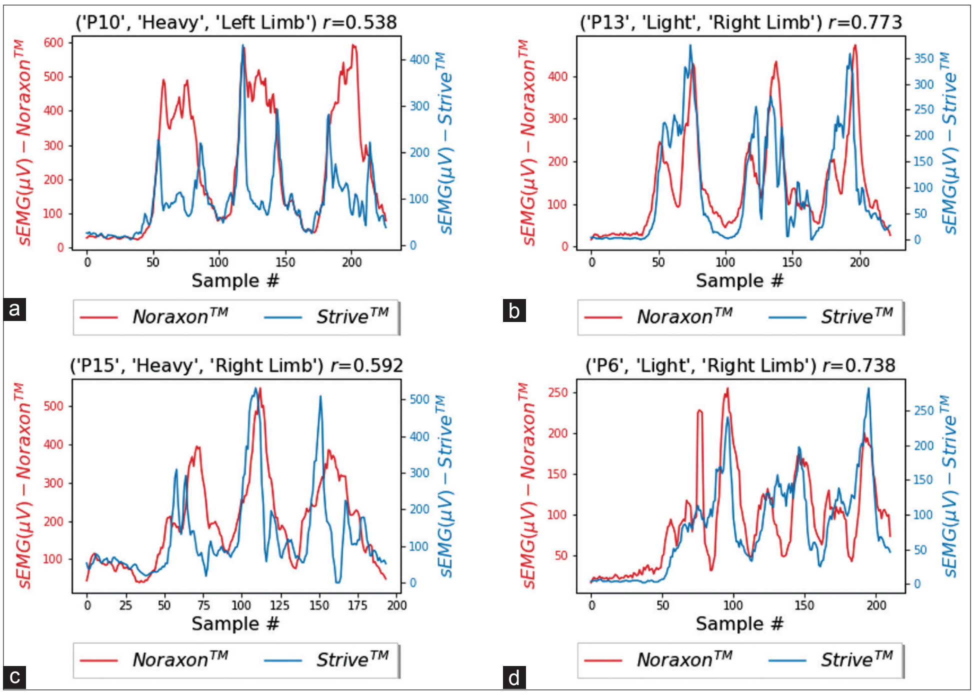

Figure 7. Outlier data identified from validity analysis, reliability analysis, and visual inspection. (a) Data for participant 10 (P10) for the left limb during the heavy weight trial, (b) Data for participant 13 (P13) for the right limb during the light weight trial, (c) Data for participant 15 (P15) for the right limb during the heavy weight trial, and (d) Data for participant 6 (P6) for the right limb during the light weight trial

could produce less accurate sEMG data. More testing with more participants performing various athletic movements will be needed to test this assumption, however.

CONCLUSIONS

Results indicate that the Strive™ system can be utilized as a valid and reliable system under ideal circumstances. Analysis of outlier data indicated that proper lubrication of the sensor electrodes is imperative to acquire accurate data from the sEMG shorts and that the shorts must be a proper fit for the athlete in order to best detect muscle activity. Lastly, improved results for the medium and heavy weight over the light weight trials indicate that there may be a threshold in muscle activation that should be reached in order for the Strive™ shorts to accurately track the data. If care is not taken to use and fit the shorts properly, the athlete and coaching practitioner could be at risk of collecting data that will go to waste due to an insufficient detection of muscle activity.

AUTHOR CONTRIBUTIONS

Conceptualization, E.J.; Data curation, D.H., J.R., E.J.; Formal analysis, S.D., D.S., E.J., H.C., L.S., J.E.B.; Investigation, S.D., D.S., J.E.B.; Methodology, S.D., D.S., E.J.; Project Administration, E.J., R.F.B.V., H.C., L.S., J.E.B., B.K.S.; Resources, E.J., R.F.B.V., H.C., L.S., J.E.B., B.K.S.; Software, S.D., D.S.; Supervision, E.J., R.F.B.V., H.C., L.S., J.E.B., B.K.S.; Validation, S.D., D.S., J.E.B.; Visualization, S.D., D.S.; Practitioner feedback, T.L., L.O., C.C., D.B., B.B., A.P.; Practitioner feedback curation, R.F.B.V., T.L.; Writing—original draft, S.D., D.S., E.J., H.C., R.F.B.V.; Writing—review and editing, S.D., D.S., E.J., R.F.B.V., H.C., L.S., J.E.B., B.K.S.

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DECLARATION OF INTEREST

The author, Reuben F. Burch V, has a former student who is now an employee at Strive™. The authors, to the best of their ability, have presented the data in an unbiased manner to judge the performance of the product. No free products or financial support were contributed to the researchers from Strive™.

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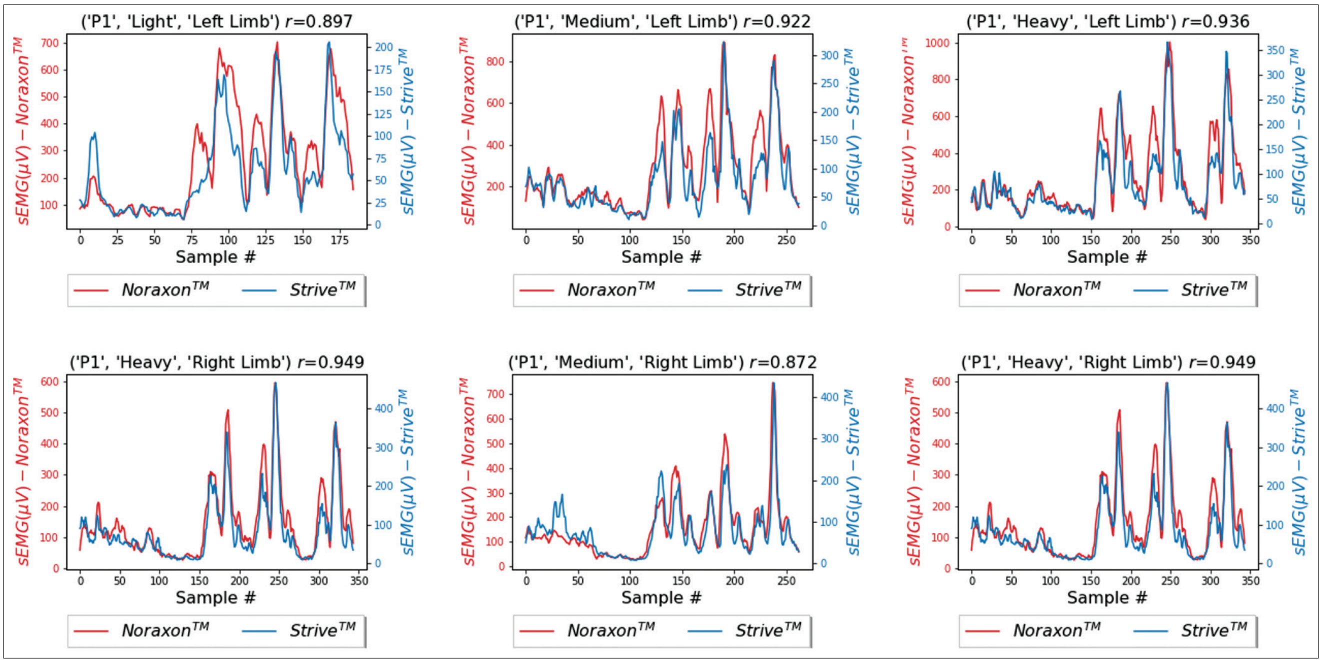
APPENDIX

In this part, the plots of sEMG measurements from the Strive™ Sense3 and NORAXON™ systems are illustrated for each trial with light, medium, and heavy weights and separated by the measurements from the left and right limbs.

Participant 1:



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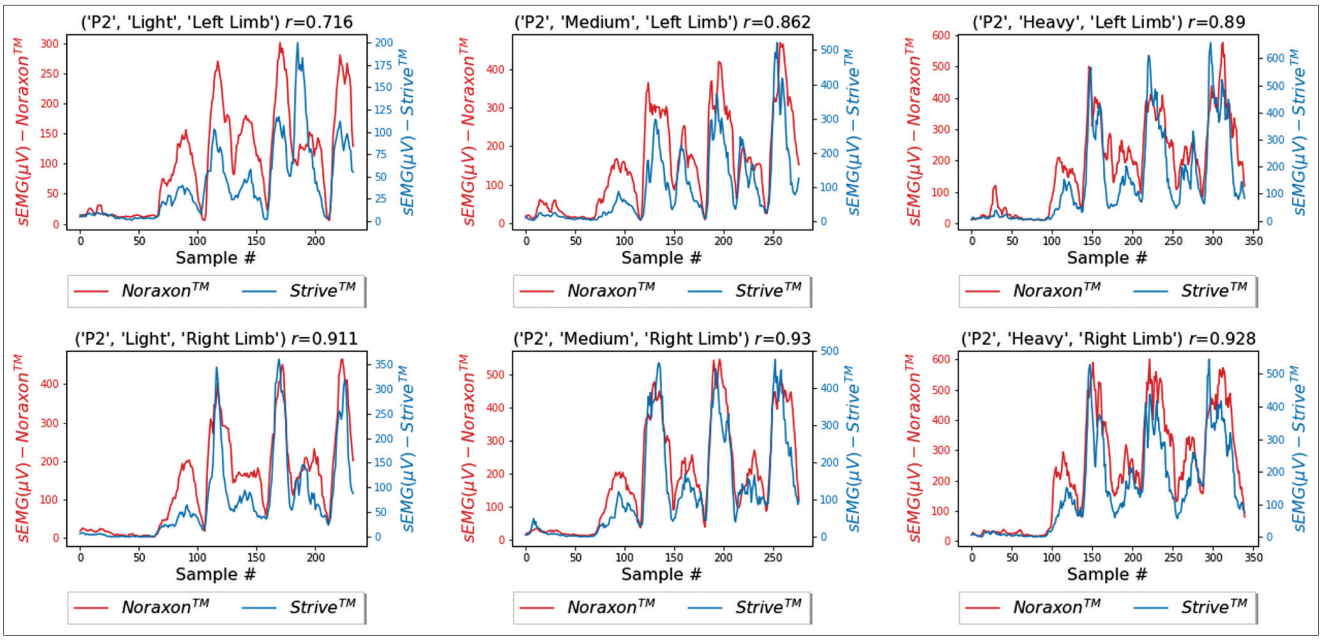

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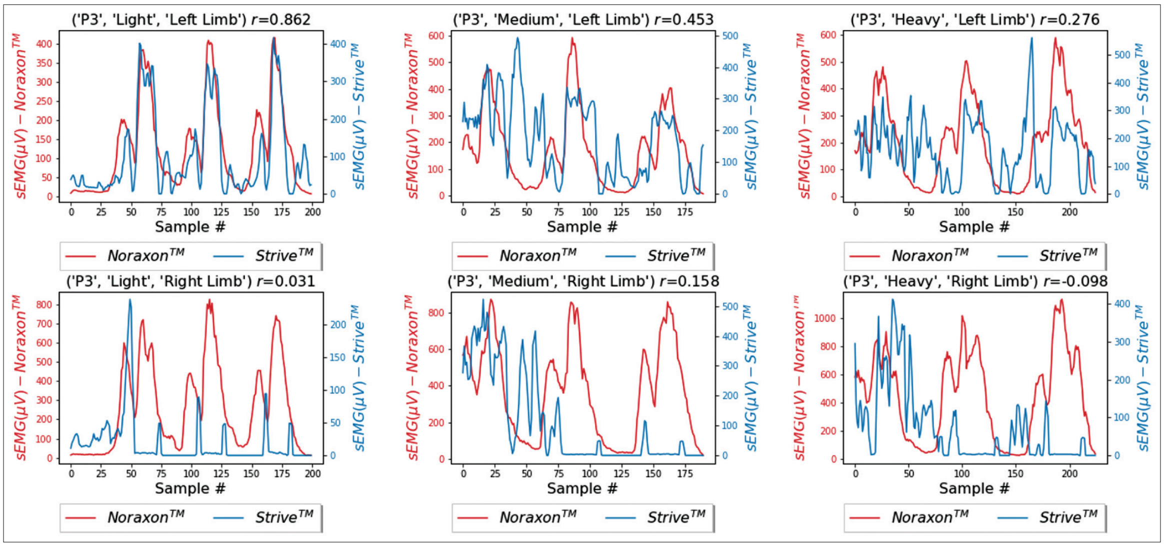

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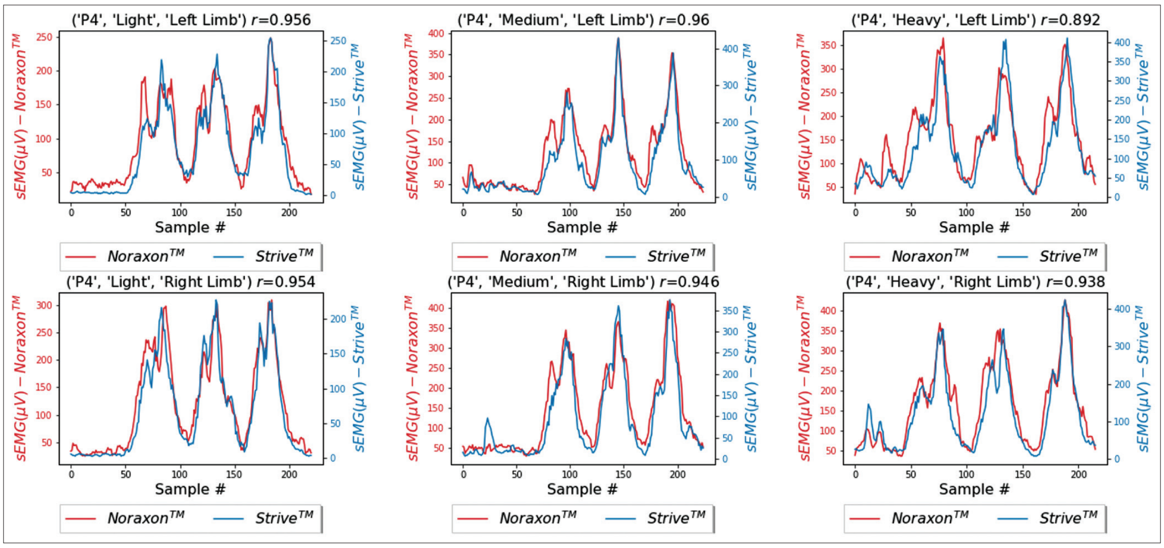

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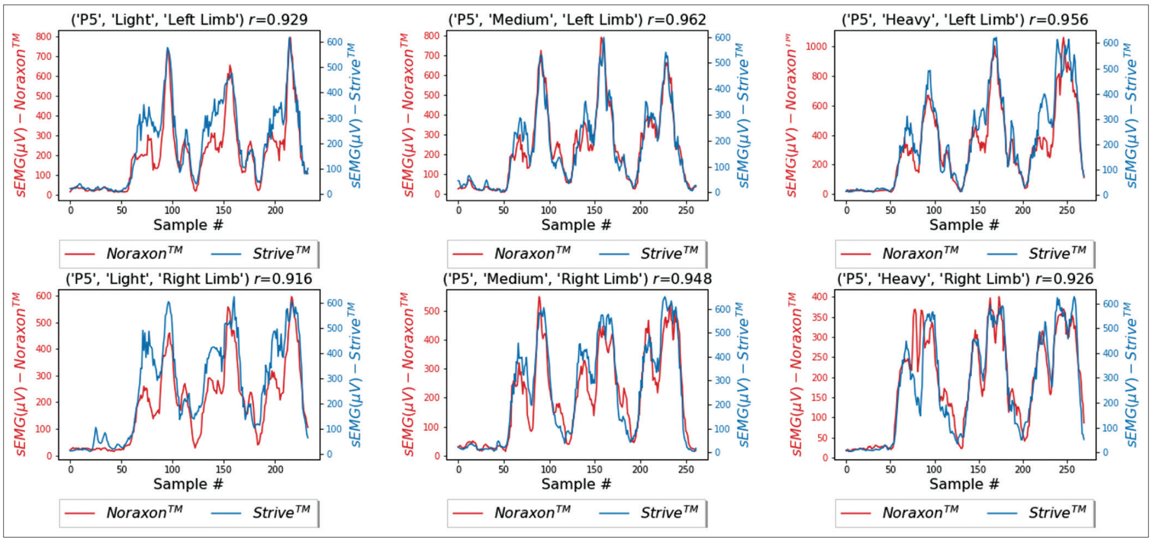

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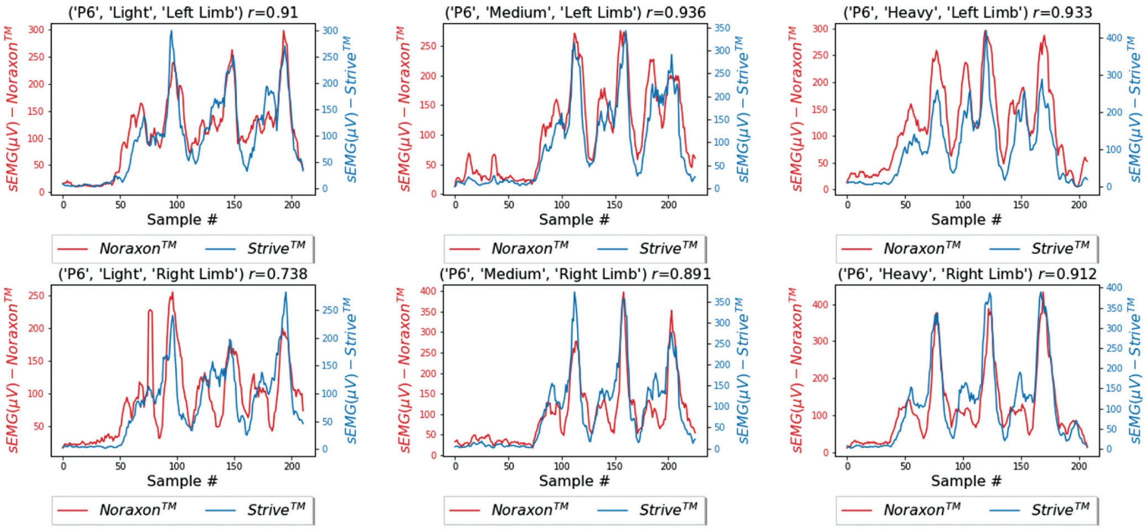
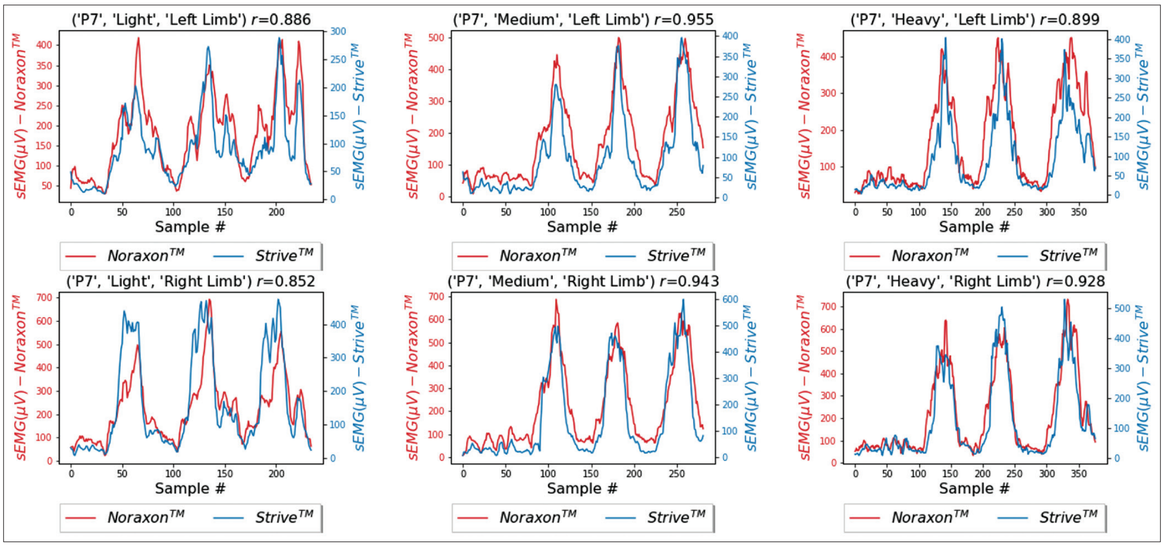


Participant 7:



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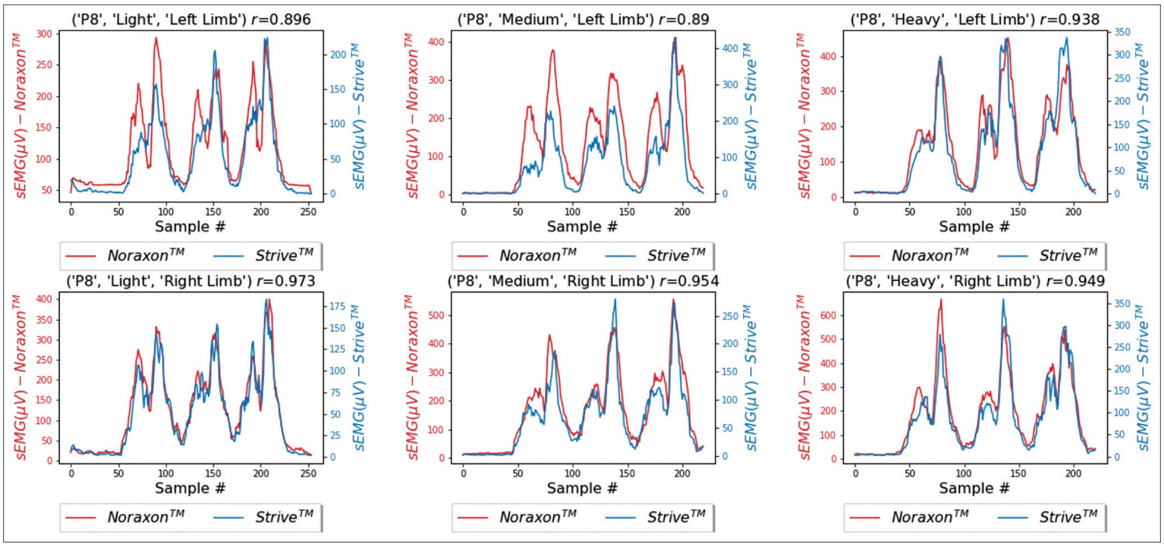

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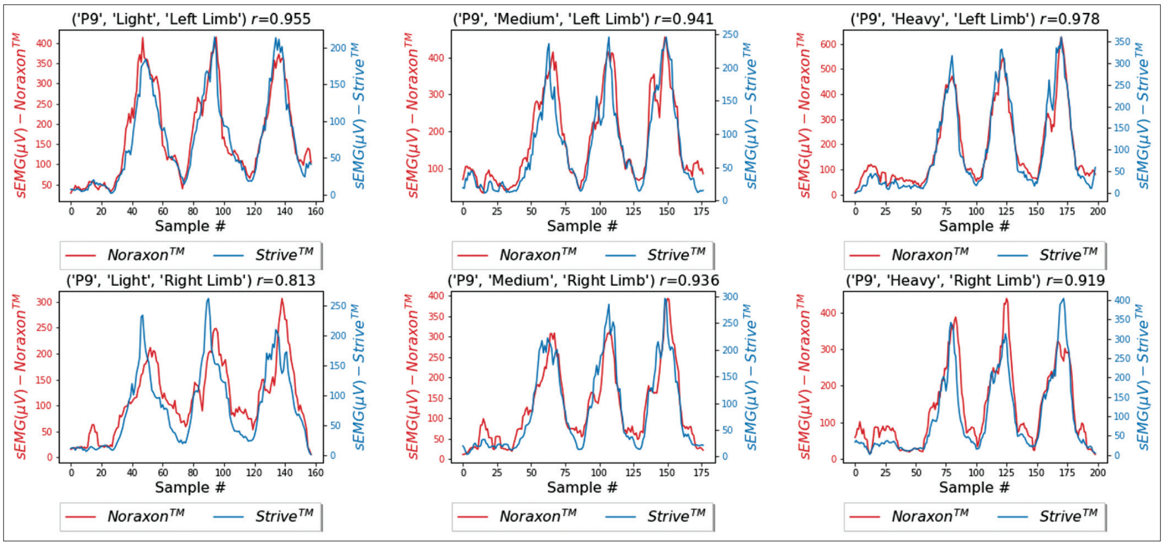

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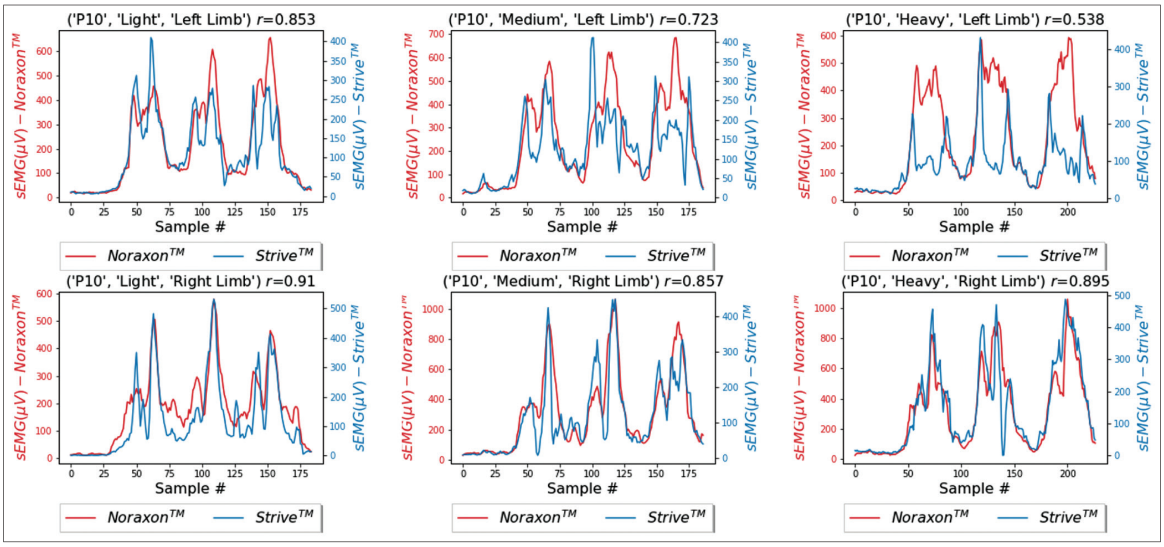

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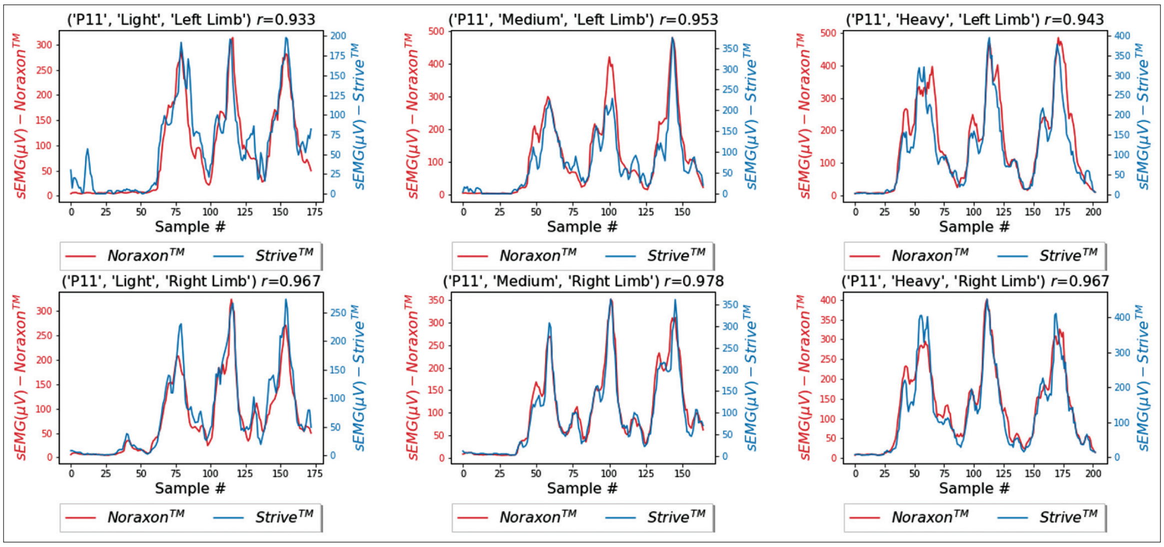

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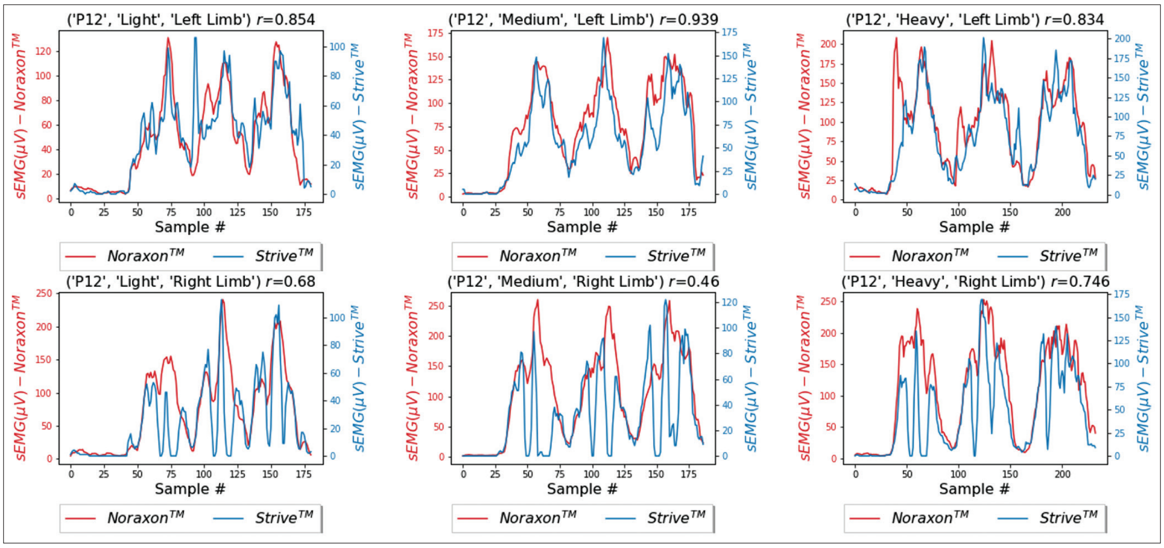

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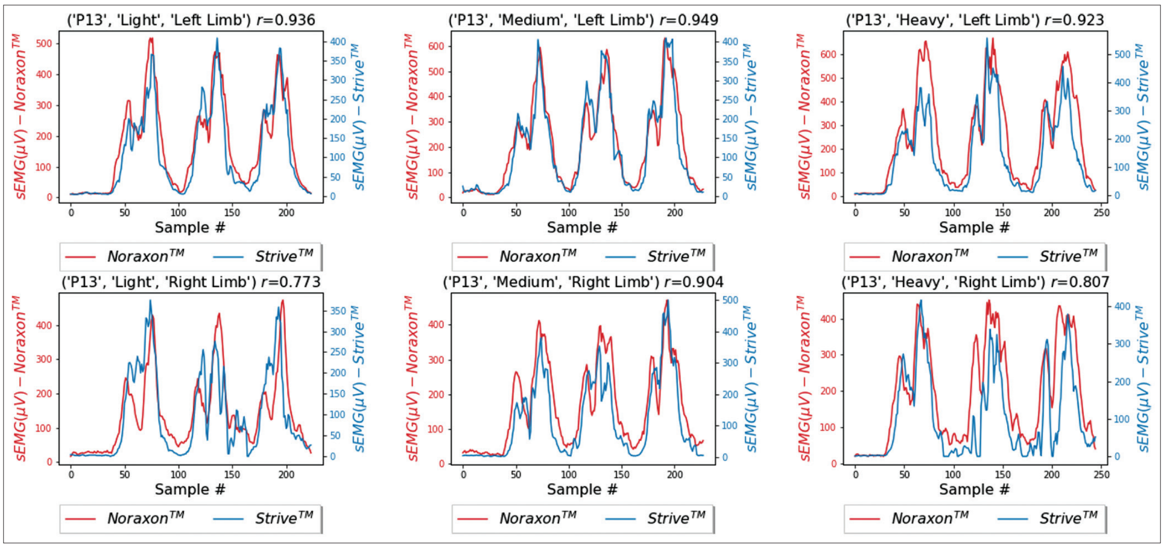

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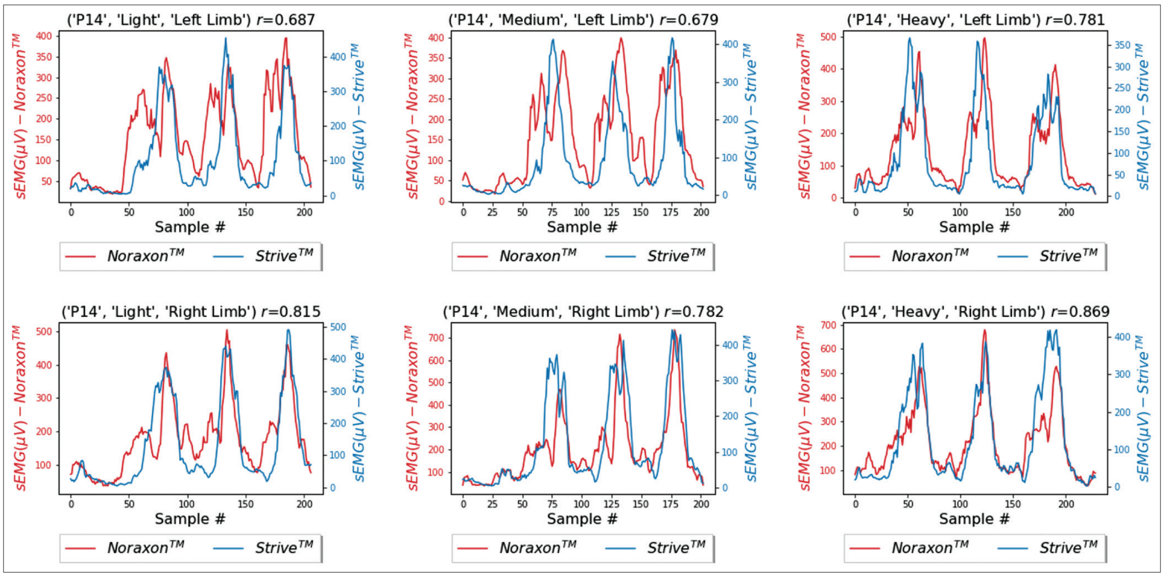

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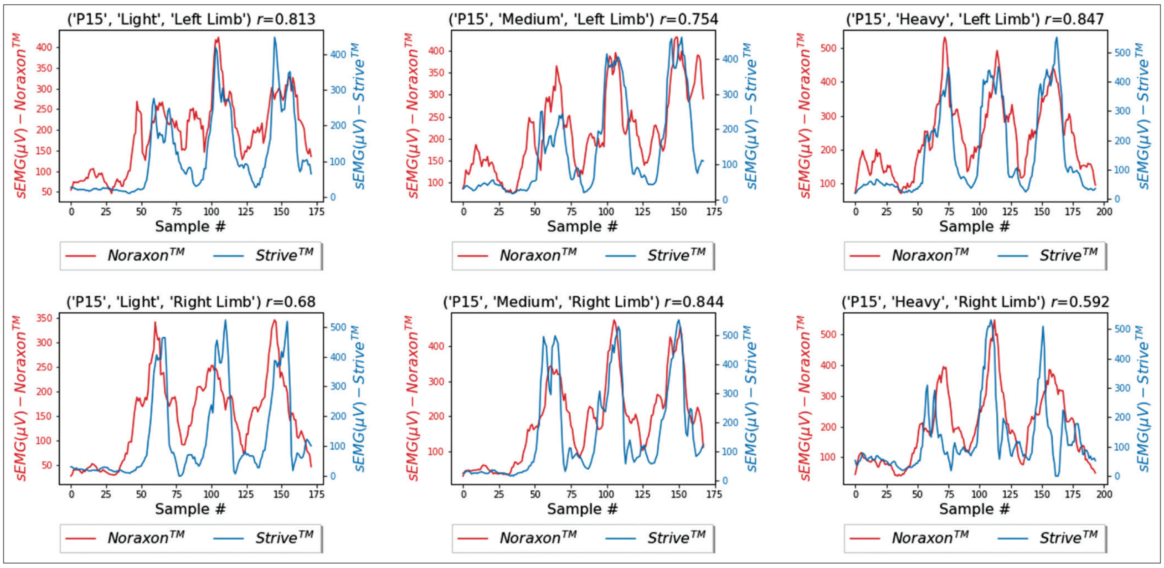

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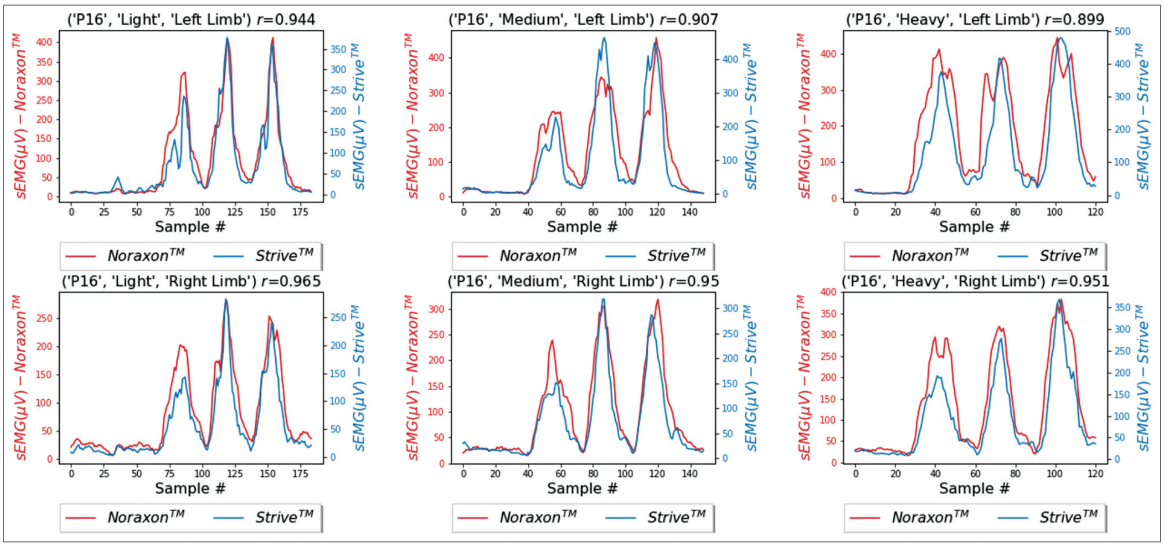

Participant 17: