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Wavelet analysis reveals differential lower limb muscle activity patterns long after anterior cruciate ligament reconstruction

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Abstract

The purpose of this study was to test whether differences in muscle activity patterns between anterior cruciate ligament-reconstructed patients (ACLR) and healthy controls could be detected 10 to 15 years post-surgery using a machine learning classification approach. Eleven ACLR subjects and 12 healthy controls were recruited from an ongoing prospective randomized clinical trial. Surface EMG signals were recorded from gastrocnemius medialis and lateralis, tibialis anterior, vastus medialis, rectus femoris, biceps femoris, and semitendinosus muscles. Muscle activity was analyzed using wavelet analysis and examined within four sub-phases of the hop test, as well as an average of the task as a whole. K-nearest neighbor machine learning combined with a leave-one-out validation was used to classify the muscle activity patterns as either ACLR or Control. When muscle activity was averaged across the whole hop task, activity patterns for all muscles except the tibialis anterior were identified as being different between the study cohorts. ACLR patients demonstrated continuous muscle activities that spanned take-off, airborne, and landing hop phases versus healthy controls who displayed timed and regulated islets of muscle activities specific to each hop phase. The most striking features were 25-50% greater relative quadriceps intensity and approximately 66% diminished biceps femoris intensity in ACLR

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[6]AUTHOR'S CONTRIBUTION

P. Zandiyeh: Conceptualization, data processing, analysis, formal statistical analysis, manuscript writing, review & editing, visualization, and interpretation. **L. Parola:** data preparation, data processing, writing the manuscript, review & editing; **BC. Fleming:** resources, methodology, review & editing, supervision, funding acquisition.; **J.E. Beveridge:** conceptualization, project administration, funding acquisition, review & editing.

[7]CONFLICT OF INTEREST

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patients. The current findings are in contrast to previous work using conventional co-contraction and muscle activation onset EMG measures of the same dataset, underscoring the sensitivity and potential of the wavelet approach coupled with machine learning to reveal meaningful adaptation strategies in this at-risk population.

Keywords

Anterior cruciate ligament reconstruction; neuromuscular function; electromyography; wavelet analysis; k-nearest neighbor

1 INTRODUCTION

Anterior cruciate ligament (ACL) reconstruction remains the clinical gold standard for restoring joint stability, re-establishing knee function, and enabling a return to sport following ACL injury (Chalmers, et al., 2014; Siegel, et al., 2012). However, compensatory muscle activity patterns (Hurd and Snyder-Mackler, 2007), altered neuromuscular coordination (Moraiti, et al., 2010) and persistent abnormal biomechanics (Delahunt, et al., 2013; Deneweth, et al., 2010; DeVita, et al., 1998; Georgoulis, et al., 2010; Salem, et al., 2003; Xergia, et al., 2011) have been reported in ACL reconstructed (ACLR) patients, even after completing rehabilitation protocols and returning to pre-injury activities. It remains unclear whether these functional changes are permanent, to what degree they remain different from uninjured persons, and whether subtle differences in muscle activity could modulate abnormal joint motions and the long-term risk of post-traumatic osteoarthritis (PTOA).

To this end, surface electromyography (EMG) has been a valuable tool to quantify muscle activity across various healthy and injured cohort studies (Hanson, et al., 2008; Ortiz, et al., 2008; Shanbehzadeh, et al., 2017; Wikstrom, et al., 2008). Nevertheless, one of the challenges with EMG analyses is that extracting discrete outcomes (e.g., muscle activation onset, co-contraction indices, and normalized EMG signal amplitude) from continuous and complex electrical signals requires *a priori* selection of temporospatial variables. Consequently, much of the higher-order EMG signal information, such as the interrelationship between the magnitude, timing, and frequency, is discarded, creating the possibility that crucial physiologic muscle activity differences may remain undetected. This variable selection and/or omission problem is especially relevant to patient populations where subtle neuromuscular deficits may persist in ways we do not yet fully understand, such as long-term ACLR patients (>10 years post-reconstruction).

Conversely, wavelet analysis decomposes EMG signals into a series of overlapping non-linearly scaled wavelets that are superimposed to create a visual representation of the complex underlying signal attributes (von Tscharner, 2000). In this way, muscle EMG events with a given intensity at one frequency can be simultaneously compared to others at different frequencies over a continuous time frame. Although not yet widely adopted in orthopedic biomechanics, the wavelet approach has been applied previously in studies of muscle activation patterns during running (Nuesch, et al., 2012; Von Tscharner and Goepfert, 2006; von Tscharner, et al., 2003), walking (Kuntze, et al., 2015b; Mohr, et al., 2019; von Tscharner and Valderrabano, 2010), stair climbing (Kuntze, et al., 2015a), and single-leg squats (Bishop, et al., 2020). In these works, supervised classification algorithms were applied to the wavelet patterns to characterize and compare continuous EMG wavelet properties.

Here, we applied wavelet analysis to the EMG signals recorded during a single leg hop-for-distance activity. We tested the hypothesis that differences in wavelet EMG patterns between ACLR and healthy controls could be detected at 10-15 years post-surgery and classified using a machine learning approach.

2 METHODS

2.1 Subjects and Criteria

Twenty-two subjects were recruited from an ongoing prospective randomized controlled trial that has followed ACLR and matched healthy control subjects over the past 15 years (NCT00434837) (Akelman, et al., 2016; Fleming, et al., 2021; Fleming, et al., 2013): 11 ACLR subjects (5 males, 6 females; age = 34.7±9.9 years; BMI = 27.7±4.0; 11.9±1.3 years post-follow-up) and 11 healthy control subjects (7 males, 4 females; age = 38.8± 6.5 years; BMI = 25±3.2; 11.9±1.3 years post initial follow-up). At the time of parent study enrollment, ACLR subjects had sustained a unilateral ACL injury and underwent ACL reconstruction surgery. Subjects were excluded if they had a history of a previous knee injury to the ipsilateral or the contralateral limb, significant concomitant injury to ligaments or menisci, or demonstrated degenerative joint changes. Control subjects were matched to ACLR subject demographics at the time of parent study enrollment and were invited to participate if they had no prior ligament or meniscus injury. The index limb was randomly assigned such that the left/right designation matched the proportion of the ACLR group. None of the control subjects had sustained a significant knee injury requiring surgery at the time of the present EMG sub-study. Because of the difficulty of recruiting a sufficient number of female control subjects from the parent study at 10-15 year follow-up, a single female control subject with similar demographics to the present sub-study was recruited. The total number of subjects analyzed was n=23. Detailed subject demographics are described in Table 1, as was previously reported (Behnke, et al., 2021).

2.2 Study Protocol

After providing Institutional Review Board-approved informed consent, data were collected as subjects performed a single leg hop for distance test (i.e., “hop test”). The goal of the test was to take-off and land on the ipsilateral leg while striving to achieve a maximum jump distance without taking a compensatory step to regain balance. The hop test was chosen because of its frequent application in ACLR rehabilitation programs to gauge global neuromuscular function (Rudolph, et al., 2000; Xergia, et al., 2015; Xergia, et al., 2013) with excellent reliability (Barber, et al., 1990; Bolgla and Keskula, 1997; Noyes, et al., 1991). Each subject completed three practice trials from which the average hop distance was calculated. The distance for the final hop test was adjusted to 65% of the average trial distance to ensure subjects could land reproducibly at the center of the force plate. Surface EMG electrodes were placed over seven lower limb muscles: Gastrocnemius Medialis (GM) and Lateralis (GL), Tibialis Anterior (TA), Vastus Medialis (VM), Rectus Femoris (RF), Biceps Femoris (BF), and Semitendinosus (ST). EMG placement sites were shaved and cleaned with rubbing alcohol. Bipolar Ag/AgCl EMG electrodes (Noraxon, Scottsdale, AZ) were placed on the skin overlying the muscle bellies. EMG signals were collected wirelessly at 3000 Hz (Desktop DTS, Noraxon, Scottsdale, AZ). During the hop test, movements of the lower extremities were recorded at 125 Hz using an eight-camera optical motion capture system (Oqus 5+, Qualisys, Goteborg, Sweden), and the ground reaction forces were collected at 3000 Hz using a force platform (9260AA, Kistler USA, Hudson, NY). All collection modalities (i.e., MoCap, EMG, and Force platform) were time-synchronized, and MoCap and Force data were filtered as described previously (Behnke, et al., 2021; Coats-Thomas, et al., 2013; Miranda, et al., 2013).

2.3 EMG Analysis

2.3.1 Data preparation—

EMG signals were visually inspected to ensure the absence of motion artifacts or spurious EMG electrode signals. The hop test was subdivided into four distinct phases (Fig. 1). 1. Take-off (t_0-t_1): time zero (t_0) was determined by visual inspection of EMG signals and motion capture data and considered to have occurred when EMG activity and knee flexion increased abruptly. Lift-off (t_1) was calculated as the time point of minimum ankle velocity in the z-direction prior to force plate contact. 2. Airborne (t_1-t_2): was the hop phase spanning from lift-off (t_1) to contact (t_2). t_2 was defined as the time point when the vertical ground reaction force exceeded 50N (this threshold was selected to eliminate false time point identification due to ubiquitous electronic noise fluctuations). 3. Landing (t_2-t_3): was the hop phase from initial contact (t_2) to peak ground reaction force (t_3). 4. Recovery (t_3-t_4): was the phase spanning maximum vertical ground reaction force (t_3) until the subject completely stabilized (t_4). t_4 was determined by visually identifying the inflection point in the vertical center of pressure that coincided with the subject shifting their balance from their ipsilateral limb to their contralateral limb as they began to step off the force plate.

2.3.2 Wavelet Generation—

A notch filter was applied to remove the AC power line frequency (60 Hz) and its harmonics from the EMG signal, followed by a band-pass filter from 7-700 Hz (Conforto, et al., 1999). A filter bank of non-linearly scaled Gaussian wavelets was then applied to the EMG signals to calculate the muscle activity pattern with central frequencies of 7, 19, 38, 62, 92, 128, 170, 218, 271, 331, 395, 466, 542, and 624 Hz (von Tscharner, 2000). The 14 central frequencies were chosen such that they contained all muscle activity frequencies observed in this study.

2.3.3 Wavelet Analysis—

Following wavelet generation for each muscle group, data were normalized in time to 100 frames for each of the four hop phases. For each frame, EMG intensity was normalized by subtracting the mean intensity of the signal and then dividing by the standard deviation for each of the wavelet frequency bands to remove baseline differences between subjects. In this way, EMG intensities (in mV/mV) could be averaged across trials for all subjects. The normalized wavelet data were separated by ACLR or Control status, then averaged for visual and quantitative analyses between groups. To interpret wavelet visualization (Fig. 2), the frequency content was represented by the vertical shape of the wavelet representation, with the height of the object corresponding to the y-axis; signal intensity was a function of signal amplitude and was color-coded from red to white, with white corresponding to greater intensity. In the time domain, the EMG signal wavelet is reflected when an event with a particular frequency band occurred in the original signal as visualized by placement and object width along the x-axis. A more detailed description and illustration of the vectorization of the data are provided in the Supplement.

2.3.4 Average Normalized Wavelet Intensity—Average normalized wavelet EMG intensity was explored to visualize the overall continuity of muscle activation patterns. In this analysis, the normalized EMG intensity from the previous step was averaged across all hop phases (e.g., all 400 frames). The color scale from the wavelet activity patterns (e.g., colors in Fig. 3) was applied to the averaged EMG intensity amplitude.

2.3.5 k-Nearest Neighbors (k-NN) classification—To test whether wavelet muscle patterns differed between ACLR and Controls, a k-nearest neighbor (k-NN) algorithm was used to classify the patterns as either ACLR or Control. Each muscle's vectorized pattern was inputted into the k-NN algorithm once for the entire hop test and again for each hop phase separately. Varying the k-value from k=1-11 did not significantly change the classification; thus, k=1 was selected. The classification accuracy was determined by calculating the rate of correct classifications of the test points using a leave-one-out cross-validation method according to (Noirhomme, et al., 2014), which was selected to accommodate the small dataset. Additional details of the algorithm refinement are provided in the Supplement. All data processing was performed using MATLAB (2019a, Mathworks Inc., Natick, MA, USA).

2.4 Statistical Analysis

A binomial distribution test was used to test whether the classification of muscle activity patterns was significantly different between ACLR and Control subjects. According to the binomial distribution formula, the critical classification rate for this study's sample size ($n=23$) and $p<0.05$ was calculated to be 68.2%. Therefore, any muscle pattern with a k-NN classification rate greater than 68.2% indicated that differences in muscle activity were not due to chance and, therefore, statistically significant. Further details on the binomial test are described in the Supplement.

3 RESULTS

The average wavelet muscle activities for the lower limb muscles are shown in Fig. 3. The intensity patterns in GM, GL, VM, RF, BF, and ST muscle groups illustrate that the Control group exhibited more regulated and phase-specific islets of muscle activities (e.g., white dashed rectangle in ACLR GM and VM activity versus the same regions in Control patterns in Fig. 3). In contrast, ACLR subjects demonstrated greater overall muscle activity that overlapped multiple hop phases (e.g., green dashed rectangle in Control VM and RF muscle activity in Fig. 3).

Fig. 4 visually simplifies the wavelet contours presented in Fig 3, presenting the average normalized intensity for each muscle activity pattern. In addition to the more continuous muscle activity, the average VM intensity was approximately 24% higher in ACLR (1.41 mV/mV in ACLR vs. 1.17 mV/mV in Controls), suggesting that on average, this muscle remained more active in the ACLR group in this phase. In the airborne phase, the RF in ACLR subjects remained engaged on average 50% more than the controls (1.04 mV/mV in ACLR vs. 0.54 mV/mV in Controls). In contrast, overall BF activity was dramatically reduced by approximately 66% in ACLR subjects (0.55 mV/mV in Controls vs. 0.33 mV/mV in ACLRs). Likewise, GM showed approximately 20% reduced intensity in the ACLR group during take-off.

The visually dissimilar wavelet EMG patterns between ACLR and Controls (Figs. 3 & 4) were quantified using the k-NN algorithm. All muscles except TA were significantly classified when the entire hop activity was considered (Table 2). The number of muscles with significant classification rates was greatest during take-off (3/7) and airborne hop phases (4/7).

4 DISCUSSION

Analyzing EMG signals using wavelet analysis coupled with a machine learning approach made it possible to classify patterns of muscle activity unique to ACLR subjects, confirming our hypothesis. The finding that muscle activity patterns differed between the ACLR subjects and uninjured Controls contrasts our previous work where we failed to detect significant differences using conventional discrete EMG analyses in these same subjects (Behnke, et al., 2021). Based solely on muscle co-contraction indices and timing of muscle activity onset, we had previously concluded that except for the delayed timing of hamstring activity onset, ACLR muscle activity was similar to that of Controls. At the same time, only 33% of ACLR knees were deemed clinically "normal" based on International Knee Documentation Committee (IKDC) exams, suggesting that the discrete EMG variable analysis was insensitive to neuromuscular features that may be relevant to long-term ACL joint health and function. The comprehensive wavelet analysis that preserved time, frequency, and intensity domains of the EMG signals signifies the importance of retaining higher-order signal components as it altered our understanding of long-term lower limb neuromuscular function in ACL-reconstructed patients, supporting our earlier speculation.

Although ACLR demonstrated an overall increase in muscle activation intensity compared to uninjured Controls (e.g., Figs. 3 & 4), it is important to recall that the activity patterns for each muscle were normalized by subtracting the mean signal intensity and dividing by the standard deviation. Therefore, differences in activation intensity should be considered as *relative* differences in muscle activity during the hop landing and not absolute differences between ACLR and Control subjects. The meaning of the approximate 24-50% increase in relative quadriceps activation intensity illustrated in Fig. 4 suggests that relative quadriceps activity is elevated in ACLR compared to Controls. A recent meta-analysis by He and colleagues suggests that there is little consensus on the long-term muscle activity amplitude following ACLR during hop landings, with increased and decreased quadriceps and hamstring EMG activity being reported in select cases; however, the majority (79%) of studies included in the meta-analysis reported no differences compared to contralateral or healthy controls (He, et al., 2020). Our results using wavelet analysis and kNN classification at long-term follow-up contrast with these earlier findings since all ACLR muscle activity intensity patterns, except for TA, could be classified as being distinctly different from Controls. It is interesting to note that the most notable differences in quadriceps activation intensity between ACLR and Controls occurred during take-off and airborne phases, which coincides temporally with phases of peak ACL strain that occurs before toe-off and just prior to ground contact during a 1-leg hop activity (Englander, et al., 2019; Taylor, et al., 2011). The impact of these functional differences on knee contact mechanics, ACL graft integrity, and cartilage health are topics of ongoing investigation.

The wavelet analysis approach also allowed us to identify timing and pattern differences in neuromuscular activity. Looking at Fig. 4, ACLR subjects demonstrated continuous muscle activity that spanned multiple hop phases while Control subjects demonstrated islets of sporadic muscle activity. Again, these differences were most evident during take-off and airborne hop phases. The physiologic mechanisms governing these differences are unclear, but feedback and feedforward systems may be at play. While the feedback system uses sensory information to control motion with high accuracy, it requires a longer processing time (100-500ms) (Kandel, et al., 2021). Meanwhile, the feedforward system rapidly controls movement using previous experiences rather than sensory feedback (Kandel, et al., 2021). The average time elapsed during landing in this study was 30ms and is insufficient for the feedback control system to activate. Therefore, the feedforward system *should* be the modality to determine the success of landing and controlling the muscle activity during the airborne and take-off phases, which coincided with statistically different ACLR and Control muscle activity patterns (e.g., Table 2). As the feedforward mechanism is more error-prone (Kandel, et al., 2021) and most noncontact ACL injuries are related to rapid deceleration of the body upon landing (Paterno, et al., 2010), we speculate that ACL graft re-injury could be related to poor feedforward planning that is heightened by the loss of ACL proprioceptive machinery following the tear of the native ACL (Relph, et al., 2014). While further study is required to understand the relationship between EMG wavelet patterns, feedforward error, and ACL injury, this study affirms the advantages of the comprehensive wavelet analysis approach for identifying clinically important neuromuscular dysfunction in ACLR patients.

The novelty of this study was to combine wavelet analysis and the k-NN classification algorithm to identify differences in lower limb muscle activity after ACL reconstruction. The k-NN algorithm is a simple and widely used classifier for pattern recognition. As a nonparametric technique, no assumptions were made about sample distribution, so the classification was based solely on data similarity to training data. When considering all phases of the hop test collectively, the k-NN algorithm significantly classified the treatment group in 6 out of 7 muscle groups (Table 2). In other words, muscle activity patterns were uniquely different between ACLR subjects and Controls in all lower limb muscle groups studied except for the TA. Although the average normalized TA signal intensity was greater in ACLR subjects (e.g., Fig. 4), the muscle activity patterns were likely inconsistent and may be less sensitive to the ACLR condition since this muscle does not cross the knee. While the results confirmed our hypothesis that significant patterns between treatment groups could be detected and classified using a machine learning approach, translating the data complexity into clinically achievable rehabilitation targets will be topics of future work and will benefit from larger sample sizes.

The results of the current study should be interpreted while acknowledging its limitations. This study did not compare outcomes between sexes due to the small sample size and uneven distribution of males and females between the experimental groups. Previous work has reported that the timing and intensity of EMG activity differ between males and females during gait (Hewett, et al., 2005), vertical drop-jump tasks (Chappell, et al., 2007) and jump-cut maneuvers (Coats-Thomas, et al., 2013). Given these known sex-based differences, the classification rate might improve when sex is accounted for (Mohr, et al., 2019). Nevertheless, the ratio of males to females in the sample as a whole – ACLR and Controls pooled – was nearly 50/50. Although we did not classify males and females separately, because our rates of correct classification were up to 85% for some muscles (e.g., VM, RF in Table 2), both males and females were correctly classified based on their wavelet EMG pattern despite slightly less balanced M/F ratios between the experimental groups. Therefore, we reason that a perfectly balanced M/F distribution between the experimental groups would not have altered our interpretation of the present results. Another potential source of variation in EMG patterns is graft type, where three ACLR patients had a hamstring autograft while eight had a bone-patellar-bone autograft. However, longitudinal data from the parent study (Akelman, et al., 2016) and multicenter studies (Group, et al., 2018) suggest that any differences due to graft type are unlikely to be significant at 10-15 years follow-up. Nevertheless, applying our approach to ACLR patients earlier in the rehabilitation process may reveal new insights and target criteria for neuromuscular retraining that may be sensitive to graft type. While we did not perform a repeatability analysis of our approach, we reason that the most significant source of variation is the EMG recording and not the deterministic mathematical wavelet analysis or k-NN algorithm. Because others have demonstrated that routine EMG recordings during comparable ballistic movements (hurdling, jumping, cutting) are reliable and reproducible (Cavanaugh, et al., 2017; Fauth, et al., 2010), we are reasonably confident that our findings would be similarly repeatable given the standardized EMG preparation and electrode placement procedures. Lastly, the length of the hop test recovery phase was not standardized. In retrospect, the information from this final phase could have provided additional insights regarding the transition from dynamic to static postural stability systems that would probe the role of central nervous system involvement following ACLR (Needle, et al., 2017).

Our results revealed critical insights into lower limb neuromuscular activity 10-15 years after ACL reconstruction and highlighted the unique attributes of the wavelet analysis methodology that allowed these insights to be identified. Incorporating this approach into ongoing and future studies of neuromuscular function following ACL injury/ reconstruction and rehabilitation may provide new information regarding short and long-term neuromuscular adaptation strategies in this at-risk population.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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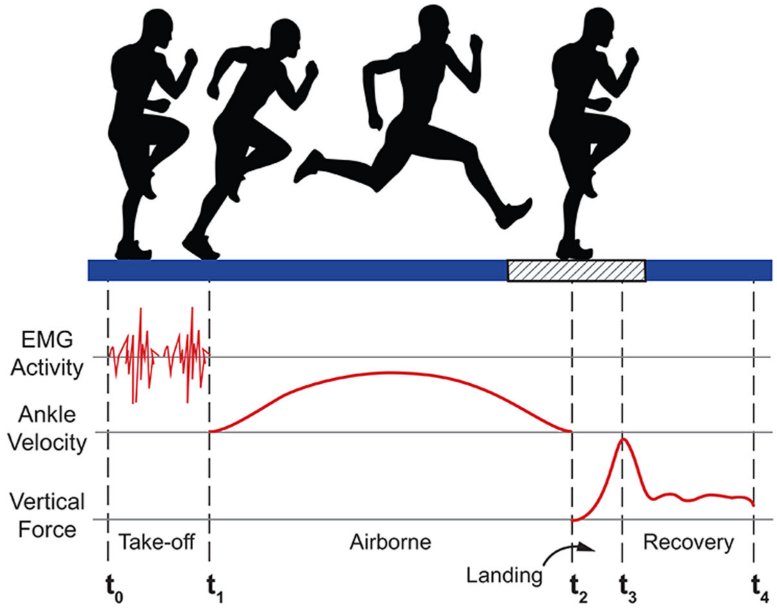

Figure 1.

All subjects performed a single leg hop for distance (hop test). Jump phases were determined from EMG, motion capture and ground reaction force data.

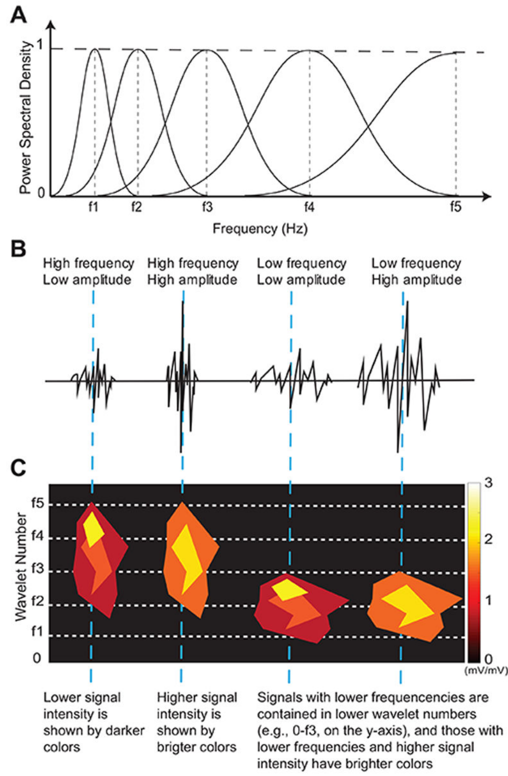

Figure 2.

An example of EMG wavelet visualization with 5 frequency bands. A. EMG signals are bandpass filtered in overlapping frequency bands (e.g., f1-5) according to their central frequency (vertical dashed lines). B. Examples of different signal frequencies and amplitudes; these parameters determine the signal intensity. C. Examples of wavelet visualization by frequency content (e.g., height of shape according to y-axis), intensity (color), and time (e.g., width of shape according to x-axis). The dashed blue lines illustrate how each wavelet in C is related to its corresponding frequency/amplitude combination shown in B.

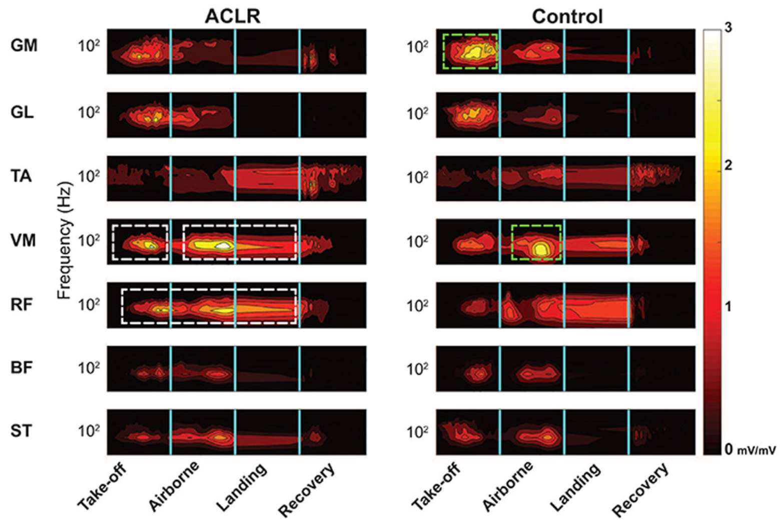

Figure 3:

Average wavelet muscle activity pattern for Control and ACLR subjects. The y-axis shows the frequency on a logarithmic scale. The normalized muscle signal intensity is shown as a colormap with brighter colors representing higher normalized EMG voltage intensities (mV/mV). White and green dashed rectangles draw attention to muscle- and hop-phase differences (see text). GM: Gastrocnemius Medialis, GL: Gastrocnemius Lateralis, TA: Tibialis Anterior, VM: Vastus Medialis, RF: Rectus Femoris, BF: Biceps Femoris, ST: Semitendinosus.

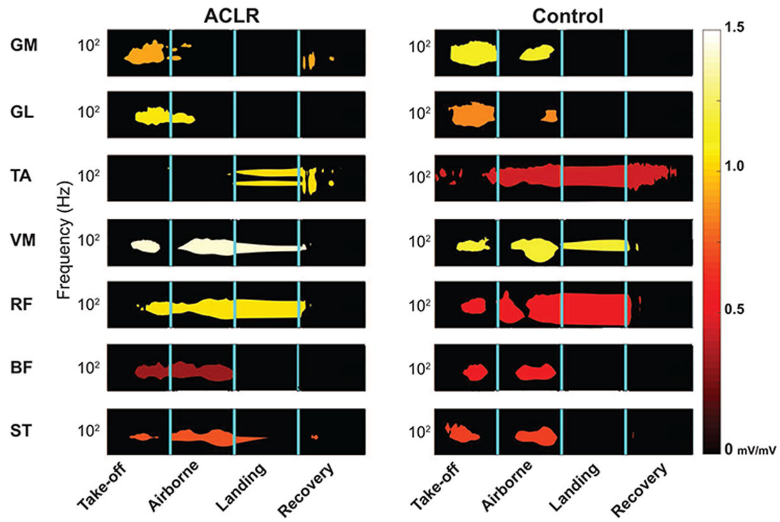

Figure 4.

Average normalized signal intensities for Control and ACLR subjects. Intensities are color-coded according to the color bar on the right, and values are expressed as mV/mV. For each muscle, the average normalized intensity is printed in white text. The shapes of the color-coded contours shown in Fig. 3 were retained to better visualize the EMG signal continuity across the entire hop test. GM: Gastrocnemius Medialis, GL: Gastrocnemius Lateralis, TA: Tibialis Anterior, VM: Vastus Medialis, RF: Rectus Femoris, BF: Biceps Femoris, ST: Semitendinosus.

Table 1.

Subject demographics and clinical hop distance at follow-up.

Sex	Subject Group	Age	Index Limb	BMI	Follow-Up Year	Hop Distance[a]
Male	ACLR	27	L	25	12	94
Male	ACLR	29	L	33	12	85
Male	ACLR	30	L	29	12	93
Male	ACLR	30	R	26	12	84
Male	ACLR	27	R	27	10	113
Female	ACLR	31	L	22	15	100
Female	ACLR	39	R	29	12	97
Female	ACLR	29	R	32	12	85
Female	ACLR	36	R	20	12	104
Female	ACLR	60	L	26	12	108
Female	ACLR	44	L	28	10	95
Male	Control	33	R	27	12	108
Male	Control	34	L	27	12	95
Male	Control	41	L	26	12	100
Male	Control	35	L	26	12	95
Male	Control	31	R	20	10	101
Male	Control	47	L	24	12	94
Male	Control	31	L	31	12	111
Female	Control	43	L	21	12	96
Female	Control	38	R	26	10	106
Female	Control	49	R	23	15	91
Female	Control	45	R	21	12	100
Female	Control	26	L	22	N/A	91

[a]Expressed as (%) difference from contralateral limb; >100 indicates greater than contralateral.

Table 2.

Correct classification rates for each muscle group based on the k-NN algorithm. A classification rate higher than 68.2% was deemed statistically significant (bolded text) according to the Binomial test. (GM: Gastrocnemius Medialis, GL: Gastrocnemius Lateralis, TA: Tibialis Anterior, VM: Vastus Medialis, RF: Rectus Femoris, BF: Biceps Femoris, ST: Semitendinosus.)

	Classification Rate (%)				
Muscle	**Entire Task**	**Take-off**	**Airborne**	**Landing**	**Recovery**
GM	**74.6%**	**74.6%**	66.7%	60.3%	**69.8%**
GL	**76.2%**	63.5%	**71.4%**	66.7%	61.9%
TA	63.5%	55.6%	**69.8%**	57.1%	58.7%
VM	**87.3%**	**71.4%**	65.1%	65.1%	57.1%
RF	**69.8%**	61.9%	**84.1%**	61.9%	58.7%
BF	**71.4%**	66.7%	58.7%	55.6%	61.9%
ST	**77.8%**	**77.8%**	**71.4%**	52.4%	61.9%