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ABSTRACT

Changes in electromyographic (EMG) parameters are used to evaluate timing, amplitude, and fatigue of muscle actions during movement. Little published data describe the reliability and precision of multiple EMG parameters, how these parameters compare to one another, and how these parameters vary between muscles. The purpose of this study was to determine the reliability and precision of four EMG parameters recorded from the legs, torso, and arm muscles during running. Fifteen well-trained male runners performed moderate-intensity treadmill running while EMG data were collected from thirteen muscles. Integrated EMG (iEMG), root mean square EMG (RMS), maximum M-wave, and median power frequency (MPF) were calculated for 25 consecutive strides. Intra-class correlation coefficients (ICC) and standard error of measurement (SEM) for each parameter were calculated for each muscle. Seven muscles displayed good reliability (ICC > 0.80) for all parameters studied. MPF was the most reliable variable, with 12 muscles having ICC > 0.80 and <6% normalized SEM. Reliability and precision differed between muscles of similar function and anatomic region. These data emphasize the need for researchers and clinicians to have reliability and precision measures for all parameters of each muscle, and demonstrates that generalizations must be used cautiously when interpreting EMG data collected during running.

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1. Introduction

Running is a popular activity that is enjoyed by people from all walks of life, from recreational fitness enthusiasts through professional athletes. Its widespread popularity is reflected in the literature, where numerous studies have examined causes of running injuries and performance limitations. Electromyography (EMG) is often used to study running physiology (Borrani et al., 2001; Hanon et al., 2005; Taylor and Bronks, 1994) and biomechanics (Andersson et al., 1997; Mann et al., 1986; Montgomery et al., 1994; Wank et al., 1998). Within-subject changes in EMG parameters for a given muscle have been used to quantify neuromuscular fatigue during running (Hanon et al., 1998, 2005; Mizarhi et al., 2000) and also describe the relationship between neuromuscular and metabolic factors (Borrani et al., 2001; Bouissou et al., 1989; Taylor and Bronks, 1994).

Raw EMG data can be processed in a number of ways to compute a variety of parameters to quantify the neuromuscular status

of a given muscle. In the time domain, changes in integrated electromyography (iEMG), root mean square (RMS), and maximum M-wave amplitude have all been described in the literature (Dimitrova and Dimitrov, 2003). In the frequency domain, median power frequency (MPF) is commonly used for evaluating fatigue (Ament et al., 1996). Though changes in a single EMG parameter are often reported (Borrani et al., 2001; Bouissou et al., 1989; Paavolainen et al., 1999), the relationship between changes in multiple parameters (Mizarhi et al., 2000; Taylor and Bronks, 1994) may be more useful for determining the physiological basis for changes in muscle activity. Additionally, some studies only report changes within a single muscle group (Bouissou et al., 1989; Hanon et al., 1998; Nagamachi et al., 2000), whereas others describe simultaneous changes in multiple muscles (Borrani et al., 2001; Hanon et al., 2005; Paavolainen et al., 1999) during running.

For differences or changes in EMG parameters to be meaningful, the EMG signal must demonstrate sufficient consistency during non-fatiguing conditions such that any changes in the signal may be interpreted as real findings. The intra-class correlation coefficient (ICC) is typically used as a measure of relative consistency (reliability) and the standard error of measurement (SEM) as a measure of absolute consistency (precision) (Weir, 2005). A number of factors may affect the reliability and precision of the EMG signal within a single running session. These include changes in muscle temperature (Bigland-Ritchie et al., 1981), alterations in

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muscle recruitment patterns (Borrani et al., 2001), and local metabolic state (Bouissou et al., 1989). Therefore, it is necessary for subjects to reach a physiologic (Poole et al., 1991) and thermoregulatory (Borrani et al., 2001; Saltin et al., 1968) steady-state when measuring the consistency of EMG parameters. Additionally, optimization of electrode–skin interactions through proper preparation and standardization of electrode placement sites (DeLuca, 1997; Zipp, 1982) are necessary for reducing error in EMG signals to optimize reliability and precision.

It cannot be assumed that a given EMG parameter has the same degree of reliability and precision for all muscles, considering some muscles act as primary movers during running (Hanon et al., 2005; Kyrolainen et al., 2005), whereas others function as stabilizers (Cromwell et al., 2001; Saunders et al., 2004). Furthermore, the leg muscles must support the body's weight, whereas the torso and arm muscles are non-weight bearing, yet actively contribute to the running motion (Hinrichs, 1990; Saunders et al., 2004). Such differences necessitate different muscle activation patterns which may result in variation in the reliability and precision of EMG parameters between different muscles.

Despite the many published papers describing changes in EMG parameters during running, there is very little reported on the reliability and precision of many of these variables (Nagamachi et al., 2000). Therefore, the purpose of this study was to quantify the reliability and precision of commonly used EMG parameters in muscles of the legs, torso, and arms during treadmill running. This information may be valuable for better interpreting data from studies which focus on within-subject changes in EMG parameters during running.

2. Methods

2.1. Subjects

Fifteen competitive male distance runners (age: 23.0 ± 4.6 years, mass: 67.4 ± 7.9 kg, height: 180.1 ± 4.6 cm) from local running clubs and collegiate teams served as subjects for this study. Subjects were required to be injury-free and performing their normal training routines for at least three months prior to enrolling in the study. Prior to testing, all subjects signed an informed consent approved by the university's institutional review board.

2.2. Testing procedures

Subjects visited the laboratory on two different occasions separated by one week. During the first session, subjects completed medical history and running injury questionnaires to determine eligibility for the study. Subjects with neuromuscular, metabolic, or cardiovascular disease or any other conditions which could alter EMG data and limit running performance were excluded from participation in the study. Qualified subjects underwent a maximal oxygen uptake (VO_2max) test while running on a treadmill wearing a telemetric metabolic system (K4b², COSMED USA Inc, Chicago, IL) and heart rate monitor (Polar USA, Lake Success, NY). The VO_2max test was used to quantify relative metabolic intensity for the second testing session and also obtain descriptive data regarding subjects' fitness levels. During the second testing session, subjects ran on a treadmill while EMG signals were recorded from thirteen different muscles using a telemetric EMG system (Noraxon Telemetry System, Noraxon USA Inc., Scottsdale, AZ).

For the first testing session, subjects were allowed to perform a 10 min warm-up of self-perceived easy running on a treadmill. Subjects then were equipped with the metabolic system and heart rate monitor and performed an incremental exercise test using a modified Åstrand protocol (Ferguson et al., 1998). Test pace was

determined by using values from a performance index (Daniels, 1998) based on recent racing performances. Subjects performed a five minute warm-up at a self-selected pace. The treadmill velocity was then increased to the test speed, which subjects maintained for three minutes. The treadmill incline was then increased 2.5 degrees every two minutes. Subjects were asked to run until volitional exhaustion while metabolic data were collected.

For the second testing session, EMG data were collected from thirteen muscles. These included leg (vastus lateralis, semimembranosus, gluteus maximus and rectus femoris), torso (erector spinae group, rectus abdominus, external oblique), shoulder/arm (trapezius, latissimus dorsi, anterior deltoid, middle deltoid, posterior deltoid, brachioradialis) muscles. Electrode placement sites were identified by using the methods of DeLuca (1997) and Zipp (1982), whereby the electrodes were placed parallel to the muscle fibers between the myotendinous junction and site of innervation.

All electrode sites were shaved, abraded, and washed with an alcohol wipe. Pre-gelled, self-adhesive bipolar silver-silver chloride electrodes (Medicotest, Inc., Rolling Meadows, IL) were then placed on each site with an interelectrode distance of 20 mm. Electrodes were secured using flexible adhesive tape. The electrodes were connected to the telemetric EMG unit. Leads were bundled together to minimize cable movement. A triaxial accelerometer module (Model 2422-025, Silicon Designs, Inc., Issaquah, WA) was adhered to the skin over medial surface of the superior portion of the tibia to later determine the time point of impact for each stride. Subjects were equipped with a telemetric heart rate monitor and were then asked to start running on the treadmill at a self-described easy pace. Treadmill speed was gradually increased within five minutes until subjects reached 70% of maximal heart rate reached on the VO_2max test. Upon reaching a consistent pace and heart rate, subjects ran for ten minutes.

2.3. Data collection

Accelerometry data and EMG data were collected at a sampling rate of 1200 Hz for twenty seconds at the start of every minute. EMG signals collected from silver-silver chloride surface electrodes passed through a single-ended amplifier with a gain of 500 to two eight channel FM transmitters. The receiver unit obtained the telemetric signals from the transmitters, where then were amplified and hardware filtered using a 15–500 Hz band-pass Butterworth filter, using a common mode rejection ratio of 130 db. Signals from the receiver were converted from analog to digital data via an analog-to-digital board (DT3010/32, Data Translation, Inc., Marlboro, MA). The digital data were collected and stored with Peak Motus 8.4 software (Peak Performance Technologies, Inc., Englewood, CO).

2.4. Data reduction and processing

All data reduction and processing was done using a using a customized Matlab (Mathworks Inc., Natick, MA) program.

Oxygen uptake data was smoothed using a 30 s moving average and normalized to total body mass. The highest value of this averaged data was designated as VO_2max .

Data from the ninth and tenth minutes of the run were used for reliability and precision calculations. Peaks in accelerometry data were used to determine the start and end points of each stride cycle. These time points were used to define a time window for each stride cycle and calculate stride rate. Twenty-five consecutive stride cycles were defined for each minute. For each stride cycle, four EMG parameters were calculated for the entire duration of the stride cycle (from impact to impact). The mean data from the 25 consecutive stride cycles were calculated for each. All EMG data

were software filtered using a band-pass filter with cutoff frequencies of 30 and 500 Hz (Ament et al., 1996; Redfern et al., 1993).

To compute iEMG, the absolute value of the band-pass filtered EMG signal was calculated to rectify the data. A low-pass Butterworth filter with a frequency cutoff of 20 Hz was applied to smooth the rectified data to obtain the linear envelope. The area under the curve was then calculated using trapezoidal integration to determine the iEMG for each stride cycle.

Root Mean Square was calculated by squaring the values of the band-pass filtered EMG signal. The mean of these squared values was then computed. The square root of this mean was then calculated to determine the RMS for each stride cycle.

Integrated EMG and RMS data were normalized to the time required to travel one meter. For each stride cycle, stride rate was divided by treadmill speed to compute the strides per meter. For each stride cycle, the iEMG and RMS were multiplied by the strides per meter to compute iEMG and RMS per meter.

Maximum M-wave was defined as the maximum magnitude of the absolute value of the band-pass filtered time-domain EMG signal.

Median Power Frequency was calculated by first applying a fast Fourier transformation to the filtered time-domain signal into frequency domain to obtain the power density spectrum (P). The median frequency of this power density spectrum was then calculated as the frequency (f) at which the integral of the left side of the spectrum was equal to that of the right side (Solomonow et al., 1990).

2.5. Statistical analysis

All statistical procedures were done in SPSS v14.0. Means, standard deviations (SD), intra-class correlation coefficients, and absolute and normalized standard errors of measurement (SEM), were calculated for each parameter for each muscle. Intra-class correlation coefficients (ICC) were calculated using the (2,1) model (Weir, 2005). The absolute SEM was estimated by subtracting the ICC value from one, taking the square root of this value, and multiplying by the SD (Weir, 2005). The normalized SEM was calculated by dividing the absolute SEM by the mean for a given parameter for each muscle to obtain a percent of the mean.

Intra-class correlation coefficients greater than 0.80 were considered to be good for research (Sleivert and Wenger, 1994) and clinical (Currier, 1984) applications. Overall means of ICC values and normalized precision values were calculated across all parameters for each muscle, and across all muscles for each parameter.

3. Results

The mean VO_2max for subjects was $71.5 \pm 6.3 \text{ mL O}_2 \text{ min}^{-1} \text{ kg}^{-1}$ and maximal heart was $188.2 \pm 10.8 \text{ beats} \cdot \text{min}^{-1}$. For the second test, the mean treadmill velocity was $3.50 \pm 0.35 \text{ m s}^{-1}$ and the mean heart rate was $136.8 \pm 13.6 \text{ beats} \cdot \text{min}^{-1}$ (72.7% of maximum).

Data for each EMG parameter for each muscle are displayed in Tables 1–4. Examples of band-pass filtered EMG data and linear envelope data are found in Figs. 1–3.

Seven muscles (semimembranosus, erector spinae, latissimus dorsi, rectus abdominus, external oblique, anterior deltoid, and brachioradialis) had $\text{ICC} > 0.80$ for each of the four parameters studied, thus meeting the criteria for very good reliability. The latissimus dorsi and brachioradialis were the only two muscles with normalized precision $< 10\%$ for all parameters. The gluteus maximus, rectus femoris, middle deltoid, and trapezius were the least precise muscles of the time-domain parameters, all with absolute SEM $> 25\%$.

The MPF was the most reliable and precise parameter measured, as all but one muscle (vastus lateralis) had an $\text{ICC} > 0.80$ and normalized precision $< 6\%$ for this parameter. Ten muscles had an absolute SEM $< 3.0 \text{ Hz}$, and the remaining three muscles were $< 7.0 \text{ Hz}$.

The iEMG was generally reliable, with only three muscles (vastus lateralis, middle deltoid, trapezius) having $\text{ICC} < 0.80$. Reliability and precision of iEMG was superior to that of RMS for all muscles except the erector spinae, latissimus dorsi, and anterior deltoid. It should be noted that these three muscles all had $\text{ICC} > 0.90$ for each parameter. Additionally, six muscles had an RMS $\text{ICC} < 0.80$. Neither of these parameters were as precise as MPF, with only five muscles $< 10\%$ for iEMG and only two muscles $< 10\%$ for RMS.

Maximum M-wave had similar overall reliability and precision to iEMG, with only three muscles (rectus femoris, middle deltoid, trapezius) having $\text{ICC} < 0.80$, but also only three muscles with normalized precision $< 10\%$.

4. Discussion

4.1. Summary of key findings

The results of this study reveal that multiple EMG parameters are reliable and precise in leg, torso, and arm muscles during running. It is clear that many muscles display excellent reliability across all parameters, with seven of the thirteen muscles having

Table 1

Integrated EMG data. Mean and standard deviations for iEMG from the ninth and tenth minute of the run are presented. The ICC, absolute SEM, and relative SEM are presented for each muscle, as well as the overall mean and SD for all muscles.

Muscle	Minute 9		Minute 10		ICC	SEM (absolute)	SEM (normalized, %)
	Mean	SD	Mean	SD			
Vastus lateralis	156.14	72.46	180.84	79.97	0.664	46.337	27.502
Semimembranosus	93.71	80.35	88.35	71.35	0.989	8.600	9.448
Gluteus maximus	52.69	39.53	53.29	34.70	0.814	17.055	32.188
Rectus femoris	119.93	66.68	140.11	89.56	0.819	38.126	29.324
Erector spinae	100.50	68.44	104.53	80.56	0.968	14.460	14.105
Latissimus dorsi	82.87	23.60	83.08	26.96	0.974	4.319	5.205
Rectus abdominus	69.99	59.35	66.99	58.57	0.986	6.972	10.179
External oblique	63.34	23.90	64.26	28.66	0.971	4.881	7.651
Anterior deltoid	41.89	23.43	47.18	25.23	0.922	7.050	15.830
Middle deltoid	66.97	30.30	63.29	23.75	0.483	21.782	33.445
Posterior deltoid	108.40	44.34	106.47	50.26	0.977	7.569	7.045
Trapezius	119.04	56.01	107.67	56.84	0.681	32.117	28.333
Brachioradialis	92.92	39.19	92.02	40.08	0.978	5.914	6.396
Overall mean					0.864	16.553	17.435
Overall SD					0.163	14.000	10.957

Table 2
Root mean square EMG data. Mean and standard deviations for RMS from the ninth and tenth minute of the run are presented. The ICC, absolute SEM, and relative SEM are presented for each muscle, as well as the overall mean and SD for all muscles.

Muscle	Minute 9		Minute 10		ICC	SEM (absolute)	SEM (normalized, %)
	Mean	SD	Mean	SD			
Vastus lateralis	0.353	0.160	0.369	0.161	0.394	0.126	34.776
Semimembranosus	0.184	0.163	0.177	0.144	0.987	0.018	10.145
Gluteus maximus	0.112	0.097	0.108	0.074	0.773	0.046	42.028
Rectus femoris	0.238	0.134	0.261	0.166	0.794	0.075	30.185
Erector spinae	0.225	0.162	0.232	0.180	0.977	0.027	11.950
Latissimus dorsi	0.157	0.043	0.156	0.047	0.985	0.006	3.698
Rectus abdominus	0.135	0.111	0.129	0.109	0.982	0.015	11.315
External oblique	0.112	0.037	0.115	0.049	0.944	0.012	10.221
Anterior deltoid	0.092	0.051	0.101	0.052	0.946	0.012	12.464
Middle deltoid	0.145	0.082	0.125	0.050	0.324	0.067	49.634
Posterior deltoid	0.221	0.104	0.195	0.062	0.555	0.069	33.312
Trapezius	0.285	0.129	0.248	0.132	0.627	0.081	30.354
Brachioradialis	0.206	0.099	0.209	0.099	0.964	0.019	9.058
Overall mean					0.789	0.044	22.242
Overall SD					0.239	0.037	14.944

Table 3
Maximum M-wave data. Mean and standard deviations for maximum M-wave from the ninth and tenth minute of the run are presented. The ICC, absolute SEM, and relative SEM are presented for each muscle, as well as the overall mean and SD for all muscles.

Muscle	Minute 9		Minute 10		ICC	SEM (absolute, mV)	SEM (normalized, %)
	Mean (mV)	SD	Mean (mV)	SD			
Vastus lateralis	1.94	0.92	2.08	0.93	0.817	0.395	19.671
Semimembranosus	0.90	0.64	0.90	0.68	0.983	0.088	9.738
Gluteus maximus	0.52	0.40	0.47	0.26	0.868	0.146	29.272
Rectus femoris	1.20	0.57	1.41	0.81	0.776	0.385	29.432
Erector spinae	1.18	1.02	1.18	0.98	0.990	0.100	8.527
Latissimus dorsi	0.75	0.26	0.76	0.28	0.941	0.068	8.961
Rectus abdominus	0.56	0.49	0.53	0.47	0.982	0.066	12.245
External oblique	0.48	0.18	0.51	0.25	0.903	0.078	15.733
Anterior deltoid	0.46	0.32	0.49	0.30	0.967	0.057	11.952
Middle deltoid	0.81	0.48	0.74	0.41	0.434	0.359	46.285
Posterior deltoid	1.12	0.47	1.09	0.50	0.973	0.082	7.421
Trapezius	1.55	0.66	1.40	0.70	0.582	0.451	30.590
Brachioradialis	1.15	0.58	1.16	0.64	0.970	0.110	9.586
Overall mean					0.861	0.184	18.416
Overall SD					0.173	0.152	11.952

Table 4
Median power frequency data. Mean and standard deviations for MPF from the ninth and tenth minute of the run are presented. The ICC, absolute SEM, and relative SEM are presented for each muscle, as well as the overall mean and SD for all muscles.

Muscle	Minute 9		Minute 10		ICC	SEM (absolute, Hz)	SEM (normalized, %)
	Mean (Hz)	SD	Mean (Hz)	SD			
Vastus lateralis	63.69	11.82	60.30	9.07	0.678	6.703	10.812
Semimembranosus	86.20	23.19	86.44	22.74	0.990	2.306	2.672
Gluteus maximus	49.91	6.02	49.81	6.77	0.850	2.621	5.257
Rectus femoris	67.80	12.01	56.31	12.41	0.967	2.269	3.977
Erector spinae	73.34	15.99	73.81	17.33	0.948	3.937	5.351
Latissimus dorsi	77.48	12.30	77.61	13.05	0.974	2.105	2.714
Rectus abdominus	49.02	11.03	48.25	9.49	0.972	1.850	3.805
External oblique	60.23	11.65	60.17	12.51	0.980	1.776	2.951
Anterior deltoid	66.77	10.48	66.29	11.16	0.963	2.145	3.225
Middle deltoid	74.19	14.27	76.23	14.77	0.907	4.497	5.979
Posterior deltoid	75.78	14.81	75.51	14.48	0.964	2.810	3.715
Trapezius	79.59	10.99	79.97	11.20	0.952	2.450	3.072
Brachioradialis	78.89	15.52	77.07	14.61	0.971	2.654	3.404
Overall mean					0.932	2.933	4.379
Overall SD					0.085	1.377	2.204

ICC > 0.90 for all four parameters, far exceeding the threshold of 0.80 for very good reliability. The vastus lateralis, middle deltoid, and trapezius were the least reliable muscles overall, with two or

less parameters meeting the criteria for very good reliability. The only frequency domain parameter, MPF, was the most reliable and precise of all parameters examined.

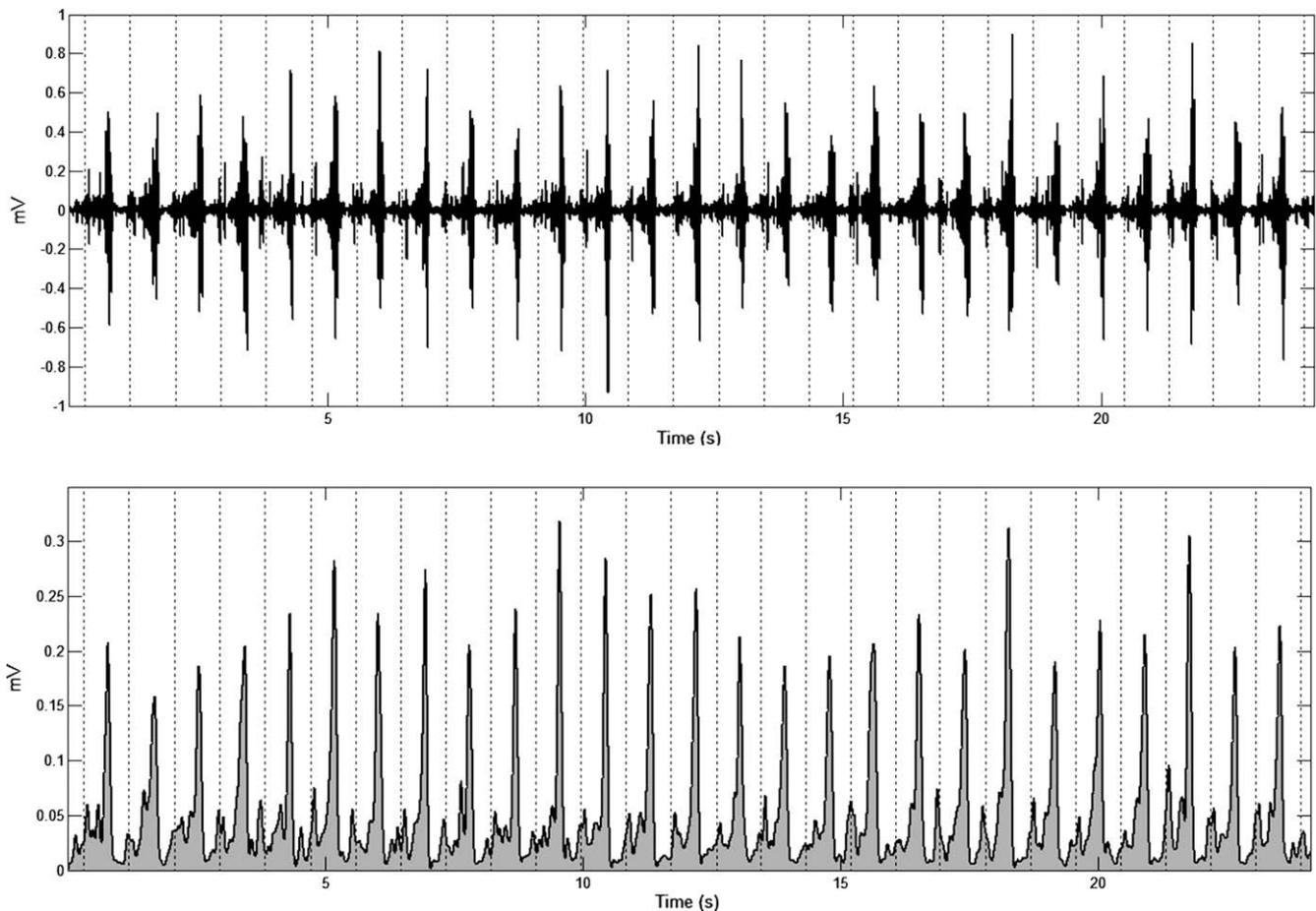


Fig. 1. Sample EMG data from a leg muscle. The top figure represents band-pass filtered EMG data and the bottom figure represents iEMG data from the vastus lateralis muscle. The dotted vertical lines represent the start of each successive stride.

Multiple variables are often interpreted together to determine the physiological nature of fatigue (Mizarhi et al., 2000; Taylor and Bronks, 1994). However, it appears there is not a solid relationship between the reliability and precision of one parameter with that of any other parameter. For instance, the middle deltoid was not reliable for iEMG, RMS, M-wave (ICC = 0.483, 0.324, and 0.434, respectively) but was reliable for MPF (ICC = 0.907). Further, it cannot be assumed that if a given parameter is considered reliable for two different muscles, it will also be similarly precise for both. For instance, the latissimus dorsi and gluteus maximus both are reliable for iEMG (ICC > 0.80). However, the latissimus dorsi has a normalized precision of 5.2% for this variable, whereas the gluteus maximus has a normalized precision of 32.2%. Therefore, it should not be assumed that if one parameter for a given muscle is reliable or precise, all parameters will be. This emphasizes the importance of knowing reliability and precision when interpreting changes in multiple variables together. If any of these multiple variables do not demonstrate sufficient consistency, investigators may not be able to make accurate conclusions about the data.

It cannot be assumed that two muscles within a region or similar function will be equally reliable. This is best observed by comparing the middle deltoid to the anterior deltoid. While both are in the same region of the body and are partly responsible for shoulder movement during running, the anterior deltoid had excellent reliability for all parameters (ICC > 0.90), whereas the middle deltoid did not, as discussed previously. A similar scenario exists between the hip extensors studied, with the semimembranosus being considerably more reliable and precise than the gluteus maximus for all parameters. The same holds true for the knee extensors studied,

namely with the rectus femoris being more reliable in iEMG and MPF (ICC = 0.819 and 0.967, respectively) when the vastus lateralis was not (ICC = 0.664 and 0.678, respectively). The discrepancy between these past two examples may be related to differences in consistency of muscle activation patterns between muscles crossing one joint (gluteus maximus and vastus lateralis) versus those which cross two joints (semimembranosus and rectus femoris) (Prilutsky et al., 1998).

It is interesting to note that the vastus lateralis was among the least reliable and precise of the thirteen muscles tested for most parameters. Electromyographic parameters of this muscle have been used quite frequently in studying fatigue during running (Hanon et al., 2005; Taylor and Bronks, 1994), as well as oxygen uptake kinetics (Borrani et al., 2001). It is not immediately clear why this specific muscle was found not to be as reliable or precise as other muscles studied in this investigation and this poor consistency appears consistent between subjects. One possible explanation is that there is considerable variation in motor control of the entire knee joint, with the vastus lateralis and medialis activated to different degrees with each stride to stabilize the patella and maintain consistent varus/valgus angles. Though this muscle has been observed to fatigue in previous studies, it is unlikely fatigue was a factor in this study, due to the relatively easy intensity of the running, the training background of the subjects, and the short period between data collection points.

Of the four parameters considered, iEMG and RMS may be considered the most similar in nature, with both being used to measure the overall amplitude and duration of the M-wave. Generally, only one of these two parameters is reported for a given

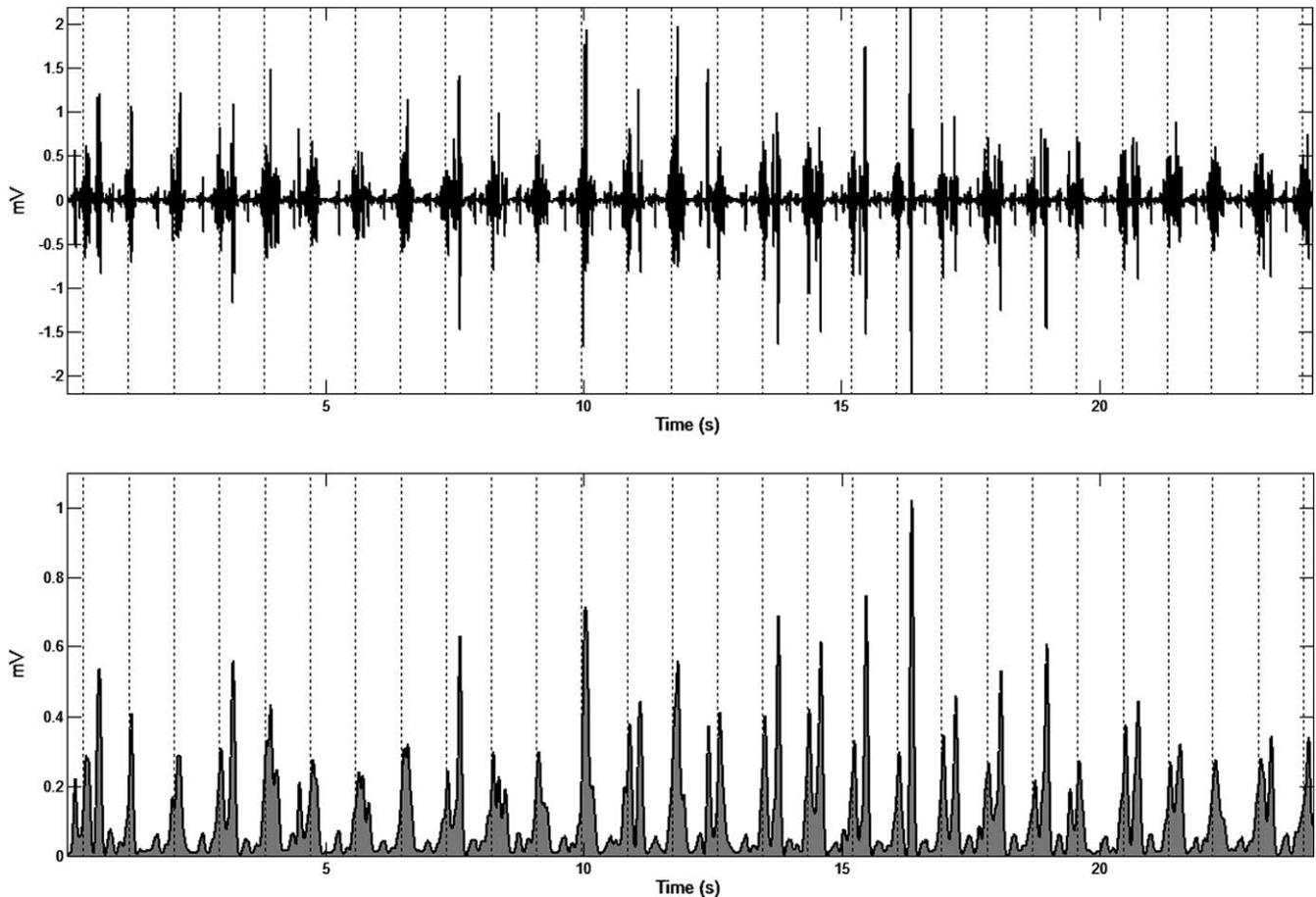


Fig. 2. Sample EMG data from a torso muscle. The top figure represents band-pass filtered EMG data and the bottom figure represents iEMG data from the rectus abdominus muscle. The dotted vertical lines represent the start of each successive stride.

study. This data demonstrated that iEMG is more reliable and precise in ten of the thirteen muscles studied, and it is still very reliable and precise in the remaining three muscles during running. Given this information, it may be recommended that iEMG is preferred over RMS when studying running.

4.2. Methodological considerations

The ICC (2,1) model used in this study accounts for systematic and random error and allows these findings to be utilized in EMG studies with similar methodology (Weir, 2005). Good reliability indicates that individual subjects demonstrate relative consistency across multiple trials within a single session, such that data from one muscle or subject can be distinguished from that of another (Weir, 2005). From this, muscles demonstrating good reliability may be used for research or clinical applications where between-muscle or between-subject differences are key. Muscles which did not demonstrate good reliability may still be used to study running, however a considerably greater number of subjects is required to reduce the risk of Type II error (Weir, 2005). It should be noted that subjects in this study were well-trained athletes with relatively low body fat. Therefore, EMG signals from these individuals would likely demonstrate greater reliability and precision than those recorded from non-athletes.

A high degree of precision may be interpreted such that data are consistent from trial to trial within a given muscle for an individual. Therefore, muscles demonstrating good precision may be used for applications where within-subject changes are the focus. With

sufficient precision, changes of an EMG parameter may be considered real, rather than an artifact of variability. In this study, normalized SEM was calculated to provide a point of comparison of the precision between multiple muscles, as mean values often differed considerably between muscles. This may be useful for determining which muscles are most ideal to use for future applications. It is important to note that all of these findings are valid for intra-session consistency but do not describe inter-session consistency, which is beyond the scope of this study.

There is considerable variability in EMG parameters for some muscles, as evidenced by large standard deviations of the mean. This reflects inter-subject variation, which may be due to differences in body composition (Nordander et al., 2003) and actual differences in motor patterns between individuals. Inter- and intra-subject variation is one reason why time-domain EMG variables are often normalized to static maximal voluntary contraction (Hanon et al., 1998; Kyrolainen et al., 2005). However, this is likely not appropriate for running, as it is a dynamic activity whereby muscle length, and therefore shape, is regularly changing. This affects EMG through soft tissue filtering, such that the average distance between the electrode site and active motor units is cyclically changing with dynamic activity (Shankar et al., 1989), such as the running stride. The concept of normalizing iEMG to stride duration was originally recommended by Hanon et al. (2005). This normalization prevents changes in stride duration from spuriously interfering with time-domain EMG and RMS data (Hanon et al., 2005). This is more functionally specific to running than normalizing to an arbitrary time period of muscle contraction at a static joint an-

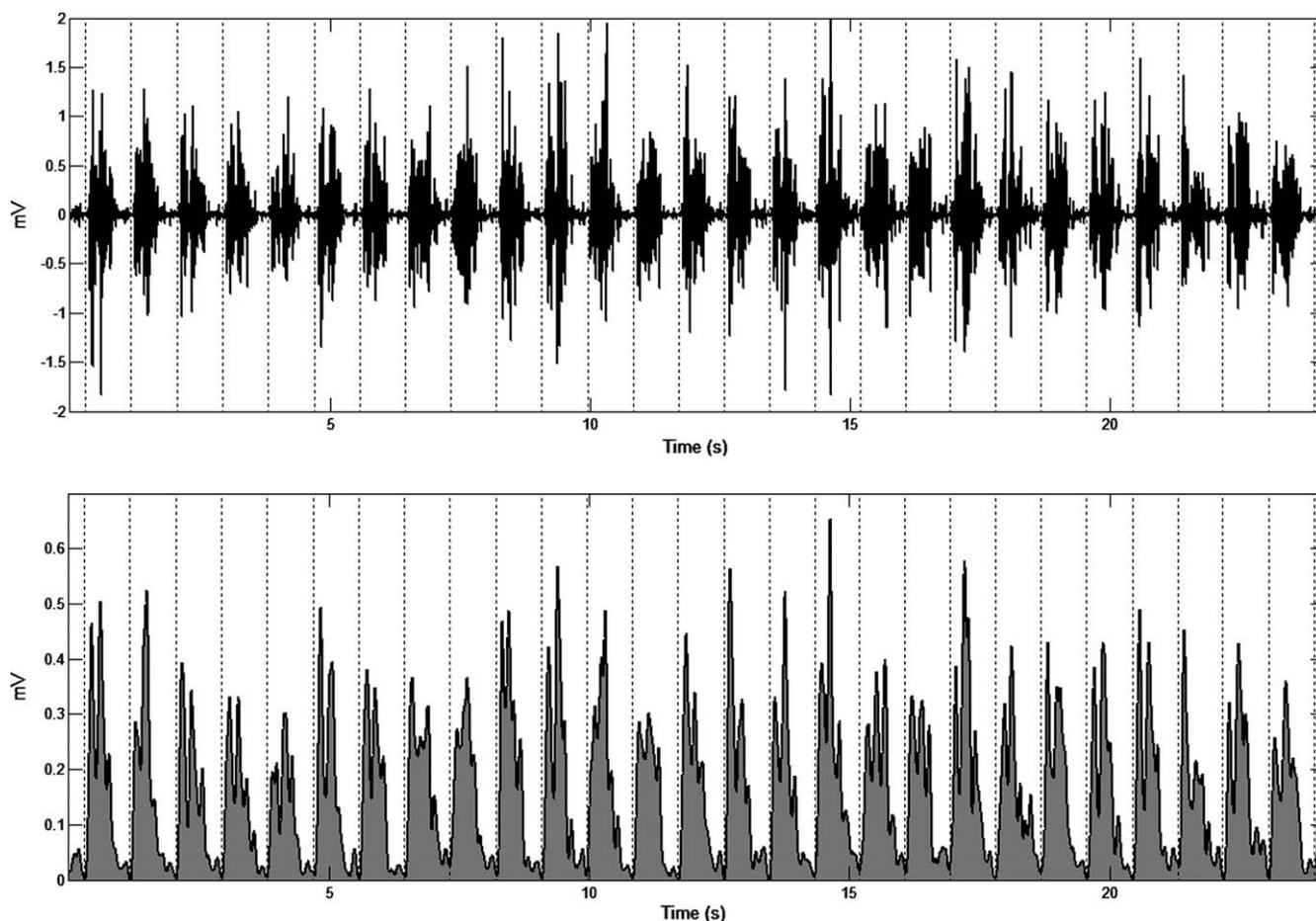


Fig. 3. Sample EMG data from an arm muscle. The top figure represents band-pass filtered EMG data and the bottom figure represents iEMG data from the posterior deltoid muscle. The dotted vertical lines represent the start of each successive stride.

gle, as in the maximal voluntary contraction method. These data demonstrate this method of normalization produces reliable and precise data for many muscles.

Many studies examining fatigue focus upon within-subject changes in EMG parameters occurring during a relatively short time period (Borrani et al., 2001; Hanon et al., 2005). For this reason, it was important to use data from two nearby time points, which is why the ninth and tenth minutes of the run were used. Heart rate data from the second test strongly suggests subjects were not running at a high relative intensity and therefore were likely in a physiological steady-state during these data collection periods (Poole et al., 1991). It would be expected that these two time points would yield very similar data if there was not considerable error within the system. This error may include noise from movement between the electrodes and the skin, as well as movement in the leads (DeLuca, 1985; Enoka, 2002). In this investigation, this error likely varied minimally between electrode sites, as the same procedures were used for each to securely adhere the electrodes to the skin and minimize movement of the leads.

It should be noted that the low-frequency cutoff of this band-pass filter was 30 Hz, a procedure which has been reported in previous running studies (Ament et al., 1996). The investigators found low-frequency noise to be present in the raw signal. This was attributable to the movement of the leads during running. While measures were taken to reduce this movement during the subject set up, it could not be completely eliminated. Additionally, electrocardiogram artifact was observed in many of the upper body muscles, and most of this is also located below 30 Hz (Redfern et al., 1993). Because nearly the entire EMG signal is above this fre-

quency (Basmajian and DeLuca, 1985), this method of filtering provided for a cleaner signal with minimal data loss (Redfern et al., 1993).

When examining the biomechanical differences between treadmill and overground running, conflicting results have been reported, however very little of this has focused upon EMG specifically (Wank et al., 1998). Studies investigating EMG differences between treadmill and overground activities have reported minimal differences for both running (Wank et al., 1998) and walking (Lee and Hidler, 2008; Murray et al., 1985; Nymark et al., 2005) under both conditions. Therefore, the results from this study can most probably be extrapolated beyond treadmill running to overground running also.

4.3. Significance and applications

This information is of significance to researchers studying running performance and injuries in athletes. For instance, acute interventions, such as intentional changes in stride length which alter the EMG signal may be studied. Future studies examining EMG in relation to other variables during running, such as oxygen uptake kinetics and changes in biomechanical variables should use more than one muscle and should focus on muscles with acceptable reliability. The roles of torso and upper body muscles during running have received considerable attention anecdotally and some scientific research has been conducted in this area. For future studies to take place to better describe their role during running, it is necessary to have reliability and precision values for these EMG parameters.

An understanding of the consistency of EMG parameters may also be of value to clinicians. Clinicians may use EMG to determine muscle imbalances about a given joint or bilaterally asymmetries of a given muscle and evaluate motor control (Zwarts and Stegeman, 2003). If muscles or EMG parameters which are not reliable are used, these measurements may be erroneous and may yield inaccurate clinical decisions. By choosing EMG parameters which are reliable and precise for a given muscle, clinicians can make more accurate decisions when utilizing EMG for diagnostics.

In conclusion, these data provide a good framework for interpreting the significance of changes in EMG data. These results demonstrate reliability of one EMG parameter does not necessarily mean that another EMG parameter for the same muscle is reliable. Additionally, there is considerable variation in reliability among muscles. Lastly, these results will allow for appropriate interpretation of changes in EMG parameters of these muscles during running.

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