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Cross-comparison of time- and frequency-domain methods for monitoring the myoelectric signal during a cyclic, force-varying, fatiguing hand-grip task

Edward A. Clancy [a,b,*], Dario Farina [c,d], Roberto Merletti [c]

[a] *Department of Electrical and Computer Engineering, Worcester Polytechnic Institute, 100 Institute Road, Worcester, MA 10609, USA*
[b] *Department of Biomedical Engineering, Worcester Polytechnic Institute, 100 Institute Road, Worcester, MA 10609, USA*
[c] *Laboratorio di Ingegneria del Sistema Neuromuscolare (LISiN), Dipartimento di Elettronica, Politecnico di Torino, 10129 Torino, Italy*
[d] *Center for Sensory-Motor Interaction (SMI), Department of Health Science and Technology, Aalborg University, DK-9220 Aalborg, Denmark*

Abstract

Various conventional methods to estimate the mean and median power spectral frequencies, and amplitude of the surface electromyogram during 30–90 min, cyclic, force-varying, constant-posture contractions were *cross-compared* in an experimental trial. The aim was to determine the most appropriate algorithm implementations and reduce the total number of algorithms that need to be considered when monitoring time trends. Subjects produced hand-grip contractions in a repeated intermittent pattern until exhaustion. For all estimated parameters: analysis of contraction levels below 25% maximum voluntary contraction produced poor estimates due to high relative measurement noise; parameter reproducibility was best when comparisons were aligned to the actual force produced rather than the target force and when the biomechanics of the contraction were more consistent; and estimates were not greatly influenced by the rate of change of the force trajectory. For frequency parameters: estimates based on the short-time Fourier transform were similar to those based on time-varying autoregressive methods; longer duration analysis windows exhibited better repeatability; and simple frequency-domain noise filters were not effective in reducing the impact of measurement noise. For amplitude estimates: whitening reduced the variance of the amplitude estimate; and the best analysis window duration was a trade-off between bias (decreased with a short duration window) and variance (decreased with a long duration window).

Keywords: Electromyography; EMG; Force-varying contraction; Power spectrum; Whitening

1. Introduction

Changes in the time and frequency character of the surface electromyogram (EMG) have been well documented for sustained, constant-posture, constant-force, high-effort, short-duration (hereafter termed "static") contractions – the amplitude of the EMG *increases* and the spectrum *compresses* towards the lower frequencies [9,18,23,24]. Because of the strong association with physiologic changes within the muscle (c.f., [3,27]), surface EMG amplitude and spectral parameters offer a non-invasive marker of muscle physiology. For static contractions, the signal (EMG) is large compared to measurement noise (i.e., high signal-to-noise-ratio (SNR)) and substantial signal changes occur over several seconds. Thus, the EMG signal can be assumed to be quasi-wide sense stationary (WSS) and changes tracked via sliding an analysis window (e.g., window length of 1–5 s) across the data, repeatedly analyzing the windowed signal as if it were WSS [10]. Time-domain analysis has usually consisted of root-mean-square

* Corresponding author.
E-mail address: ted.clancy@alum.wpi.edu (E.A. Clancy).

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(RMS) or mean-absolute-value (MAV) EMG amplitude estimators, and frequency-domain analysis has used the short time Fourier transform (STFT) or time-varying autoregressive (TVAR) methods. Spectral compression has typically been quantified as a reduction in mean frequency (MNF) and/or median frequency (MDF). Each of these techniques takes advantage of the slow changes in signal character and uses a wide analysis window to reduce the variance in the tracked parameter. Further, the algorithms usually do not consider measurement noise due to the high SNR.

For most applications, however, the static contraction paradigm is prohibitive and the EMG must generally be analyzed during sustained or sporadic, force-varying, posture-varying (hereafter termed "dynamic") contractions of much longer duration. In this case, a non-stationary signal results due to the variations in EMG amplitude and joint angle (spectral changes due to fatigue occur at a much slower time scale). In addition, contractions are at lower effort levels, including levels just above muscle relaxation. Lower SNRs result, adversely influencing frequency-domain [1] and time-domain [4,7,16] signal measures. Considerably less is known about either appropriate analysis methods or the physiologic changes induced. This paper will focus on the issue of analysis methods *only*, not the actual time trends in the data. Much of the research for the dynamic case has focused on tracking frequency-domain changes in the EMG via conventional signal processing methods such as the STFT and TVAR (c.f., [10,11,20,21]). Ongoing research has explored modern time-frequency analysis algorithms (time-frequency transforms, wavelets, etc.) [2,3,26] many of which are reviewed by Karlsson et al. [17]. Recently, MacIsaac et al. [19] refocused discussion on the conventional frequency-domain analysis techniques, using a parametric model of the EMG power spectrum to show that modulation of EMG amplitude (over the physiologic range of modulation frequencies) has no substantial influence on MNF estimates computed using the STFT. Their experimental work showed that changes in MNF as a function of joint angle and muscle force tended to average for cyclic contractions wherein the distribution of MNF values are consistent cycle-to-cycle. Many tasks require repeated (cyclic) contractions that might, therefore, be applicable to analysis via the conventional methods.

In this study, continued re-examination of conventional frequency-domain analysis methods for dynamic contractions is described. The contractions were constrained to be cyclic and constant-posture, thus conventional methods can appropriately be applied. Modern time-frequency analysis methods would likely be required for more general contraction patterns. In addition, we evaluated recent advances in EMG amplitude analysis (i.e., signal whitening) that can be used to study time-domain EMG changes. With these techniques, the space of possible analysis algorithms is quite large (various techniques, window durations, noise correction schemes). Thus, our research compared a large number of processing implementations to each other to determine the most appropriate algorithm implementations and reduce the total number of algorithms that need to be considered when monitoring time trends in EMG data. The actual reporting and interpretation of the resultant trends in the measured variables from the experimental data are left for later work.

2. Methods

2.1. Experimental methods

Twelve subjects, six male and six female (mean ± SD: age = 31.4 ± 11.1 years, height = 172.1 ± 8.9 cm, weight = 75.7 ± 17.2 kg), successfully completed the experimental protocol. After subjects signed written informed consent, bipolar EMG electrode-amplifiers (Liberating Technologies model MYO115, Holliston, MA) were placed over the flexor digitorum superficialis (FDS) and extensor carpi radialis (ECR). Locations were determined as proposed by Perotto [25], then refined via palpation and EMG feedback. A third electrode-amplifier was then placed on the FDS immediately distal to the other FDS electrode-amplifier. Each electrode-amplifier signal was electrically isolated, amplified and band pass filtered (25–1350 Hz, second-order active filters). After a warm-up period and a 5 min rest, subjects performed two 2 s maximum voluntary contractions (MVCs), with a 3 min rest after each, on a hand grip dynamometer (which measured compressive grip force), as shown in Fig. 1. The average maximum dynamometer voltage provided an estimate of MVC. Subjects then squeezed the dynamometer to produce constant-posture, force-varying, fatiguing contractions, interrupted each 15 min (the interruptions lasted 2 min) for a maximum of 90 min. This contraction pattern is reminiscent of many occupational tasks that involve dexterous manipulation, assembly, etc. Subjects continued the contractions until they self-selected to stop (due to fatigue). Each 15 min of contractions was comprised of a repeated 12 s pattern. The 12 s pattern, shown in Fig. 2, was a 1 s rest, 4 s contraction "hill", 1 s rest, 3 s contraction hill, 1 s rest, and 2 s contraction hill. The contraction hills were gradual increases and decreases in grip strength in the shape of a Gaussian function. The peak of each Gaussian function corresponded to the reference contraction level, either 40% or 50% of MVC. (The target level, initially set at 40% MVC, was increased to 50% after several subjects failed to achieve sufficient fatigue in the 90 min period.) A constant-force contraction pattern at the reference level (1 s rest, 2 s ramp increase in force, 8 s reference level contraction, 1 s rest) was substituted for

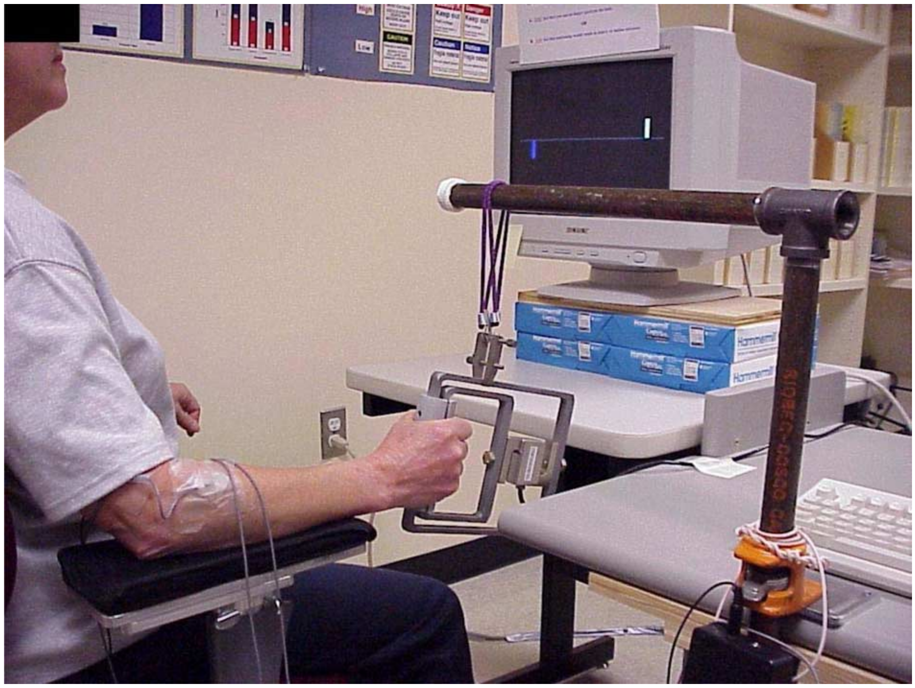

Fig. 1. Experimental apparatus. Electrodes are secured by tape over the FDS (not seen) and ECR muscles. The hand-grip dynamometer is loosely suspended and gripped by the subject. The computer screen is situated in front of the seated subject.

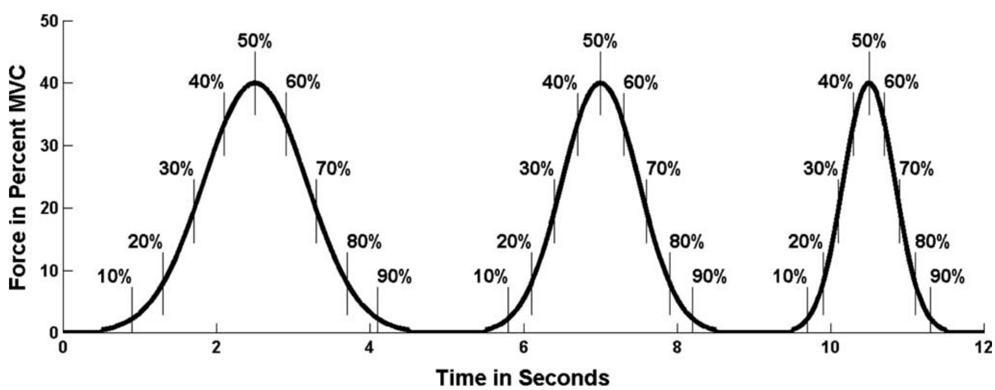

Fig. 2. Solid line shows the target force trajectory for one 12 s contraction segment. Vertical hash marks indicate the 27 locations, 9 per contraction hill, where data segments where centered for computation of parameter values. These locations correspond to 10%, 20%, 30%, . . . , 90% of the *target* contraction duration for each contraction hill.

the final 12 s pattern in each 5 min subinterval (i.e., 3 times per 15 min). This target pattern and the subject's actual force generation were shown in real-time on the computer screen, so that the subject could best match the target pattern. A 5 s constant force contraction at the reference level and a recording while subjects relaxed their arm completely were also included, as they are used to calibrate whitening filters for amplitude estimation. All EMG and grip force data were recorded by a 16-bit A/D converter (Measurement Computing model CIO-DAS1600/16, Mansfield, MA) and sampled at 4096 Hz.

The relaxation recording also provided a measure of total EMG system noise. This signal's RMS level, containing equipment noise, electrode-skin contact noise, etc., averaged $2.8 \pm 4.7\%$ of the RMS EMG at MVC (the RMS EMG at MVC was linearly extrapolated from the EMG amplitude of the 5 s calibration recording at the reference level). Recording with the two contacts of each electrode-amplifier shorted gave a measure of equipment noise alone, which averaged $0.6 \pm 0.6\%$ of the extrapolated RMS EMG at MVC.

2.2. Methods of analysis

The contraction trials were segregated into segments, each segment spanning one 12 s contraction pattern (comprised of the three contraction hills with interspersed rests). Data epochs ($\leqslant$0.5 s in duration) were centered about 27 locations, 9 locations per contraction hill, corresponding to 10%, 20%, 30%, ..., 90% of the *target* contraction duration (see Fig. 2). Note that the 10% and 90% locations were at identical target contraction forces, 10% corresponding to an upward contraction slope and 90% corresponding to a downward contraction slope, etc. The constant-force segment occurring at the end of each 5 min subinterval was not analyzed in this work. For spectral parameters, the sample mean value of each data epoch was removed and epochs less than 0.5 s in duration were zero-padded to a duration of 0.5 s (2048 samples) for analysis. In addition, the data were reprocessed using the *achieved* force level to align the center of each of the 27 data epochs. Bonato et al. [2] have shown the importance of lowering biomechanical variability when assessing frequency-domain parameters from cyclic contractions. Alignment locations for each individual hill were determined by smoothing the achieved force with a mid-point moving average filter of length equal to the epoch length, locating the peak force for a hill, and then moving down the hill (on each side) until the first occurrence of the target force level (corresponding to a target hill location) was found. For the 50% hill location, the rising portion of the hill was always selected. Note that in some contractions, the highest/lowest force level is never achieved, and the location corresponding to the closest force value must be used. This alignment method was intended to increase the biomechanical repeatability of the data analyzed from successive epochs. For the case of actual force profiles that are a pure lag or lead version of the target force, this method produces perfect alignment.

For all processing methods, epoch durations of 62.5, 125, 250, and 500 ms were investigated. For each (possibly overlapping) epoch the following parameters were computed from each EMG channel:

1. MNF and MDF using the STFT technique [10,19,22]. A "boxcar" window function was used for simplicity since the window function does not influence estimation of EMG MNFs and MDFs [22];
2. MNF and MDF using the STFT technique with noise correction, as proposed by Baratta et al. [1]. A noise PSD was estimated with the periodogram approach (using windows which overlapped by 75%) from a 5 s rest recording. In the frequency domain, the noise PSD was subtracted from the signal-plus-noise spectra estimated during the contractions (negative values, possible due to the stochastic nature of the signal, were set to zero);
3. MNF and MDF with the TVAR technique. A 10th-order AR model [10], using Burg's method, was adopted;
4. MNF and MDF with the TVAR and noise correction. Analogous to above, both MNF and MDF were re-estimated using a technique that accounted for noise. A 10th-order AR model of the noise was estimated from the 5 s rest recording;
5. Amplitude, using MAV. A channel offset (representing offsets due to the A/D converter and front-end electronics) was determined from a rest contraction and subtracted from each EMG sample in the 12 s segment. A moving-average MAV (MAMAV) processor was computed over the segment (non-causal, mid-point moving average processing);
6. Amplitude, using MAV and adaptive whitening [4–6,8,12,14–16]. The technique proposed by Clancy and Farry [4], which accounts for measurement noise, was adopted.

Given the duration of the experiment and the limited effort levels, *changes* in the frequency and/or amplitude character of the signal at the same force level, if any, would be expected to occur over a time period of many seconds or a few minutes. Therefore, one would not expect much "true" change in a parameter's value from one 12 s contraction cycle to the next. Hence, *variability* of the estimates was assessed by comparing differences between parameter values from successive 12 s force-varying contractions. That is, a parameter value computed from one of the 27 hill locations was compared to the same parameter value from the same hill location in the subsequent 12 s contraction cycle.

When parameter values were assessed, all available 12 s contraction segments (and all 27 hill locations) for all three muscles and all 12 subjects, were combined for each comparison. Similar data reduction was used when assessing parameter variability (i.e., differences in parameters between successive 12 s contraction cycles), with lower absolute differences implying less variable estimators and vice versa. All statistical comparisons used a Wilcoxon signed rank test, comparing a parameter value (or a difference between successive contractions – when variability was assessed) before and after one change in a method (e.g., a different window length, noise reduction technique, etc).

3. Experimental cross-comparison results

3.1. Biomechanical repeatability

The force dynamometer data from force-varying contractions for a given window duration, contraction location and contraction speed were normalized to the maximum target force and excised for a subject. The standard deviations from each location within a window, computed across all contractions, were averaged. This value was then averaged across all subjects to pro-

Table 1
Average of standard deviations of normalized contraction forces with and without force alignment for each contraction speed and location within the contraction hill

Hill speed	Location within contraction hill (%)				
	30	40	50	60	70
Not Aligned					
Slow	0.085	0.092	0.110	0.147	0.128
Medium	0.091	0.100	0.107	0.130	0.127
Fast	0.118	0.131	0.125	0.136	0.149
Aligned					
Slow	0.023	0.037	0.062	0.044	0.037
Medium	0.028	0.041	0.065	0.047	0.038
Fast	0.040	0.059	0.082	0.067	0.051

All results are from an epoch duration of 250 ms (results for other epoch durations were similar). A value of 1.0 corresponds to the maximum target force value (either 40% or 50% MVC, depending on the subject).

vide a measure of biomechanical repeatability. The analysis was conducted with and without force alignment for each window duration.

Table 1 shows the results when the analysis window was 250 ms (results were similar for the other window durations). The average errors varied between 2% and 15% of the total force range. Alignment reduced the average error by factors of 2–4. Errors were consistently lower on the upward phase of the contraction, when compared to the same target force level on the downward phase (e.g., comparing the 30% vs. 70% hill locations and the 40% vs. 60% locations). Errors increased considerably for the fastest contraction speed.

3.2. STFT vs. TVAR techniques

Sample data from a 12 s contraction sequence are shown in Fig. 3. "Unphysiologically" high MNF, and to a much lesser extent MDF, estimates were observed at the lower contraction level hill locations. These locations would have the highest relative proportion of noise in the recorded EMG signal. MNF or MDF estimates above 300 Hz were arbitrary considered out of the physiological range. At the lowest contraction levels (the 10% and 90% hill locations), up to 8% of the MNF estimates (and 1% of the MDF estimates) were above 300 Hz. More unphysiologic results were seen with the shorter epoch durations. At these low contraction locations, noise correction actually *worsened* the problem. Closer examination suggested that at low contraction levels and/or short epoch durations, some of the analyzed signals contained predominantly noise. Force alignment of the epochs, however, greatly reduced the number of unphysiologic measurements at all contraction levels (with and without noise correction) by factors of

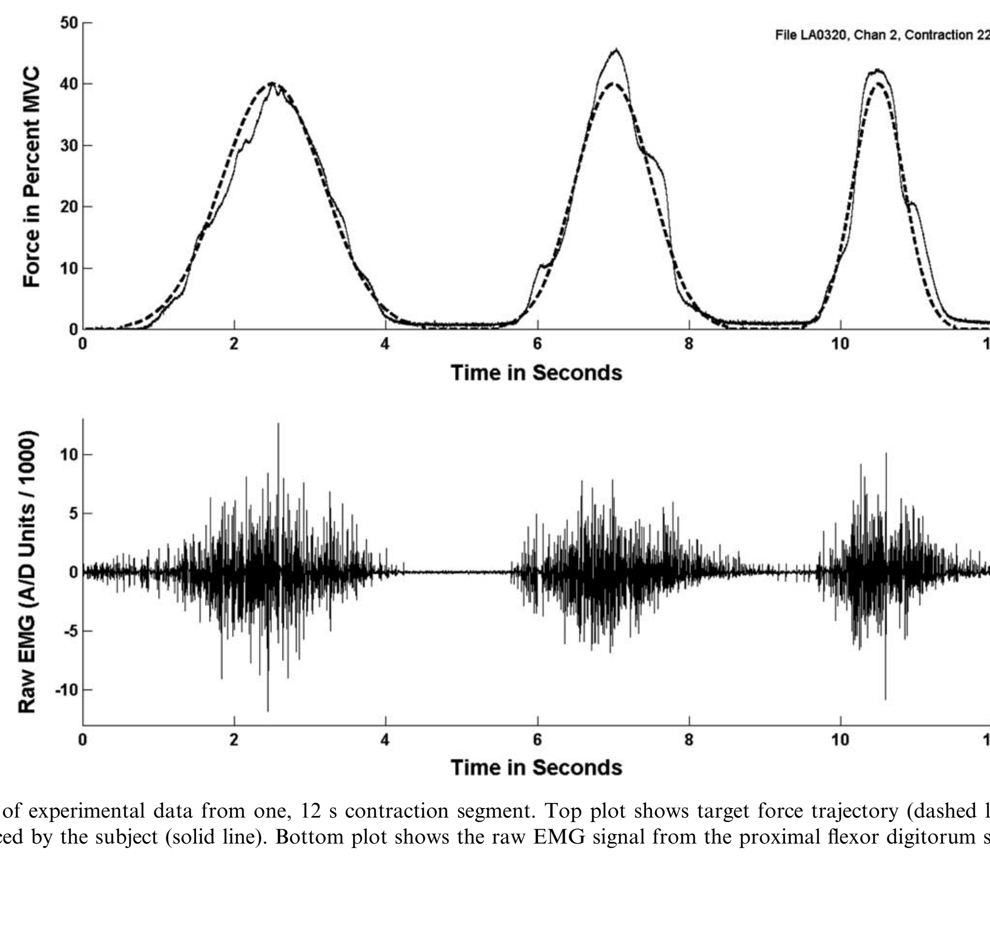

Fig. 3. Example of experimental data from one, 12 s contraction segment. Top plot shows target force trajectory (dashed line) and actual force trajectory produced by the subject (solid line). Bottom plot shows the raw EMG signal from the proximal flexor digitorum superficialis recording location.

Table 2
Average ± standard deviation in the absolute differences (in Hz) between MNF/MDF estimates from consecutive force-varying contractions as a function of location within the contraction hill and method of force alignment for the STFT spectral estimation technique

STFT	Location within contraction hill (%)								
	10	20	30	40	50	60	70	80	90
MNF not aligned	37.1 ± 83.3	19.2 ± 38.0	15.1 ± 20.8	14.7 ± 18.2	16.3 ± 23.7	18.9 ± 33.4	23.9 ± 47.7	38.3 ± 82.6	63.1 ± 117
MNF force aligned	25.9 ± 67.8	16.2 ± 28.6	14.2 ± 15.6	14.2 ± 15.0	14.5 ± 15.3	14.9 ± 15.8	17.6 ± 19.6	24.0 ± 33.7	45.7 ± 90.6
MDF not aligned	28.1 ± 74.6	19.4 ± 33.3	17.4 ± 20.2	17.2 ± 18.4	18.2 ± 21.9	19.7 ± 29.5	23.1 ± 42.2	32.1 ± 73.9	45.3 ± 108
MDF force aligned	24.4 ± 71.0	18.1 ± 29.3	16.9 ± 17.6	17.0 ± 17.0	17.3 ± 17.4	17.6 ± 17.6	19.5 ± 20.3	24.5 ± 31.3	36.4 ± 85.4

Results are computed across all subjects, window durations, noise correction methods and contraction speeds.

$2–10^{+}$. All reductions in unphysiologic values were statistically significant ($p < 10^{-6}$) for all hill locations and noise correction methods.

Table 2 lists the average ± standard deviation of the absolute differences between MNF/MDF estimates from consecutive force-varying contractions as a function of location within the contraction hill and method of force alignment for the STFT spectral estimation technique (similar trend results were found for the TVAR spectral estimation technique). Errors were larger at the lower contraction levels and during the downward hill slope. Force alignment always provided a statistically significant error reduction ($p < 0.01$). The MDF estimates exhibited less error at these extremes. Spectral parameters computed from the 10% and 90% hill locations were considered unreliable and excluded from further analysis. Additionally, only force-aligned epochs were used as they were consistently more reliable.

Parameter estimates were next compared directly between the STFT and TVAR methods, as a function of window duration and noise correction method. A bias ($\leqslant$6.4 Hz) existed between the methods. This bias was removed before comparison, since most applications of spectral information only track relative changes in parameter values. Table 3 shows the absolute differences between the methods. These differences were small and decreased with increasing window length ($p < 10^{-3}$ for all increases between adjacent window durations, except when comparing uncorrected MNF estimates between the 125–250 ms and 250–500 ms durations). At a window duration of 500 ms, the average difference in the MNF estimates without noise correction was less than 1 Hz. Noise correction increased the differences at each window duration ($p < 10^{-6}$ for all pair-wise comparisons). Because of the similarities between the STFT and TVAR results, only STFT results will be reported further.

Next, the influence of window length was evaluated by assessing differences in consecutive force-varying contractions. Results are presented in Table 4. For both MNF (which had the lowest errors overall) and MDF estimates, all errors decreased as window duration increased ($p < 10^{-6}$ for each pair-wise comparison from adjacent window durations). Again, estimates with spectral noise correction performed poorer ($p < 10^{-6}$ from each pair-wise comparison with matching window duration and frequency parameter). Although not shown in the table, the average MNF ranged between 130 and 140 Hz and the average MDF ranged from 105 to 113 Hz, depending on the window length and hill location (all results without noise correction).

Comparison was next considered within and between the three contractions hills. From Table 2, we have already seen that less variable estimates occurred during the rising edge of the contraction, presumably because the contraction dynamics were more reproducible therein. The influence of contraction speed was evaluated by comparing consecutive force-varying contractions as a function of the three hill speeds for both noise correction methods. For MNF estimates, the average difference between successive contractions ranged from 13.6 to 18.7 Hz. For a fixed hill location, the largest difference in

Table 3
Average ± standard deviation differences (in Hz) between STFT and TVAR spectral estimates (after removing the mean difference) as a function of window duration and noise correction method for the middle five contraction levels

Parameter/noise correct?	Window duration (ms)			
	62.5	125	250	500
MNF, None	4.6 ± 5.3	2.3 ± 2.7	1.3 ± 1.6	0.8 ± 1.0
MNF, Corrected	5.7 ± 16.1	3.6 ± 14.3	2.8 ± 9.7	2.5 ± 7.9
MDF, None	7.4 ± 6.0	5.7 ± 4.5	4.3 ± 3.4	3.4 ± 2.6
MDF, Corrected	8.6 ± 17.0	6.8 ± 15.6	5.4 ± 10.4	4.3 ± 7.9

Table 4
Average ± standard deviation of the absolute differences (in Hz) between MNF/MDF estimates from consecutive force-varying contractions as a function of window duration for the STFT spectral estimation technique for the middle five contraction levels

Parameter/noise correct?	Window duration (ms)			
	62.5	125	250	500
MNF, None	21.9 ± 19.3	15.7 ± 14.1	11.9 ± 11.0	9.4 ± 9.4
MNF, Corrected	23.1 ± 24.7	16.5 ± 17.6	12.4 ± 12.3	9.8 ± 10.2
MDF, None	25.0 ± 20.7	18.7 ± 15.7	14.1 ± 12.4	11.0 ± 10.1
MDF, Corrected	26.6 ± 27.2	19.7 ± 19.4	14.8 ± 13.8	11.5 ± 11.2

Table 5
Average ± standard deviation of the absolute differences (in % MVE) between amplitude estimates from consecutive force-varying contractions as a function of location within the contraction hill and method of force alignment

Method	Location within contraction hill (%)								
	10	20	30	40	50	60	70	80	90
Not aligned	5.4 ± 8.3	6.0 ± 8.7	6.7 ± 9.3	7.6 ± 10.2	8.3 ± 10.8	8.5 ± 10.8	8.2 ± 10.5	5.2 ± 7.3	3.8 ± 8.2
Force aligned	4.5 ± 7.6	4.9 ± 7.4	5.6 ± 8.3	6.6 ± 9.4	7.5 ± 10.1	7.5 ± 10.1	7.2 ± 9.7	3.9 ± 7.3	3.0 ± 6.5

Results are computed across all subjects, window durations, whitening methods and contraction speeds.

these averages as a function of the hill speed was less than 2 Hz. Comparison between speeds was not statistically significant when comparing adjacent hill speeds ($p > 0.01$). In any case, the strength of any differences was very small. Similar results were found with MDF.

3.3. EMG amplitude

EMG amplitude results were initially compared between force alignment methods. Table 5 lists the average ± standard deviation absolute differences between amplitude estimates from consecutive force-varying contractions as a function of location within the contraction hill. The maximum differences occurred at the largest contraction locations (the contraction peak is at the 50% hill location, as shown in Fig. 2). For all hill locations, a statistically significant decrease in the absolute difference occurred using force alignment ($p < 10^{-6}$ for all comparisons between aligned and unaligned results at each location), leading to lower averages and standard deviations. Thus, less variable amplitude estimates resulted when the data were aligned to the force profile actually produced by the subject rather than the target profile. Only force-aligned amplitude estimates were considered further.

Table 6 shows the average ± standard deviation absolute differences between amplitude estimates from consecutive force-varying contractions (matched by contraction level) as a function of window duration and whitening method. The average differences were lower for whitened processing (vs. unwhitened) at the 62.5 and 500 ms window durations and equivalent at the 125 and 250 ms window durations. In all cases, the standard deviations of the errors were lower with whitening. For whitened processors, differences decreased with increased window duration. For unwhitened processors, differences were best (minimum) at 250 ms, and poorer the further away from this duration. All pair-wise differences in adjacent cells (whitened vs. unwhitened, or different window lengths) were statistically significant for all comparisons discussed in this paragraph ($p < 10^{-6}$).

Lastly, Table 7 shows the average ± standard deviation absolute differences between amplitude estimates from the same location, but different speed hills within the same 12 s contraction as a function of location within the contraction hill (results are computed across all subjects, window durations and whitening methods). Lower EMG levels corresponded to lower variance EMG estimates, as has been observed previously in the literature (e.g., [5]). All differences compared within a cell (one hill speed vs. another at the labeled location) were statistically significant ($p < 10^{-6}$), except all comparisons at the 80% location ($p > 0.01$). If we compare adjacent hill speeds (slow vs. medium and medium vs. fast) vs. the two extremes (slow vs. fast, in the middle row of the table), the extremes consistently led to larger absolute differences. However, these differences added a

Table 6
Average ± standard deviation of the absolute differences (in % MVE) between amplitude estimates from consecutive force-varying contractions as a function of window duration and whitening method

Method	Window duration (ms)			
	62.5	125	250	500
Unwhitened	8.0 ± 11.8	6.6 ± 10.2	5.6 ± 8.9	6.1 ± 8.6
Whitened	7.5 ± 9.8	6.5 ± 8.7	5.7 ± 7.9	5.0 ± 7.1

Results are computed across all subjects and contraction speeds with the force profiles aligned.

Table 7
Average ± standard deviation of the absolute differences (in % MVE) between amplitude estimates from the same location, but different speed hills within the same 12 s contraction as a function of location within the contraction hill

Hills	Location within contraction hill (%)								
	10	20	30	40	50	60	70	80	90
Slow vs. medium	4.5 ± 7.6	4.9 ± 7.0	6.5 ± 10.0	9.0 ± 10.9	10.1 ± 11.7	7.2 ± 9.1	5.0 ± 6.5	3.9 ± 7.6	3.0 ± 6.7
Slow vs. fast	5.1 ± 7.7	6.6 ± 7.6	8.5 ± 11.0	10.4 ± 12.4	11.4 ± 13.0	8.1 ± 9.8	5.7 ± 7.1	4.2 ± 7.8	3.2 ± 6.0
Medium vs. fast	4.9 ± 6.6	6.0 ± 7.5	7.4 ± 8.9	9.5 ± 10.7	10.5 ± 11.2	7.3 ± 9.0	5.1 ± 6.0	3.7 ± 5.6	2.8 ± 5.5

Results are computed across all subjects, window durations and whitening methods.

maximum of 2% MVE to the errors – a rather small relative change.

4. Discussion

This work examined the relative merits of various technical implementation details of conventional frequency- and time-domain parameters of the EMG signal during a cyclic, force-varying, fatiguing hand-grip task. The analyses focused on the relative improvement in the parameter values (or their variability) resulting from changes in the computational methods. Study of the actual time trends produced by this data set is left as future work. The research adds to the body of scientific knowledge of EMG change during fatiguing contractions since the existing literature has little or no studies whose methods (a) describe optimized (whitened) time-domain (EMG amplitude) parameters, (b) quantify the improvement available when successive contractions are aligned, (c) cross-compare different degrees of non-stationarity (i.e., different contraction speeds for the same contraction profile), and (d) cross-compare the effect of additive measurement noise on spectral estimates during force-varying conditions.

For spectral parameters, it was found that the STFT and TVAR methods are roughly equivalent for estimation of MNF and MDF, particularly when noise-corrupted data regions are avoided and relative frequency changes are monitored. For the force trajectory studied, forces at or above 25% MVC were preferred. MNF and MDF for forces below 25% MVC were artifactually inflated (because the MNF and MDF frequency of noise is much higher than that of EMG), as noted by Baratta et al. [1]. MNF estimates were more susceptible to noise than MDF estimates, as noted previously by Hof [13]. Alignment of the epoch-by-epoch analysis to the achieved force was found to be essential in preserving SNR by assuring that the analyzed segment indeed occurred during the contraction phases of the experiment rather than the rest phases. Alignment also greatly increased the repeatability when scanning across epochs. Although noise reduction seems preferred on theoretical grounds, it does not alter spectral parameters when the SNR is large (i.e., the force level is above 20–30% MVC). At very low SNRs, simple subtraction in the frequency domain may be inadequate, since epoch-by-epoch estimates of the EMG spectrum have too high a variance – spurious, unphysiologic frequency parameter estimates can result. Thus, it seems best to avoid entirely analysis of such portions of a data record, analyzing only those portions in which the SNR is high enough that noise removal makes no difference. Epoch length does not have much influence on the bias of frequency parameters [19], but longer windows greatly reduced their variance. Thus, longer windows are preferred (at least up to 500 ms), limited by avoidance of contraction levels below 25% MVC. The upward slope of the contraction provided more reproducible results, presumably because the biomechanics were more repeatable. Contraction speed did not influence the error in the spectral estimates, confirming that the non-stationarity due to amplitude modulation did not significantly affect the estimates [19].

For amplitude estimation, low SNR at the lower contraction levels was problematic. Adequate estimates were achieved for forces at or above 25% MVC. Alignment of the epochs to the achieved force always improved performance and, thus, should always be incorporated. Whitening consistently reduced parameter variance, although it can introduce a small bias to the amplitude estimate. Note that if the true EMG spectrum is changing (e.g., compressing) throughout the course of an experiment (or the background noise level is changing), then the shape of the adaptive whitening filters may need to do so also. In this work, the filters were fixed during a calibration phase occurring at the beginning of the experiment, and did not account for such changes. The optimal window duration requires a trade-off between bias (arising from EMG amplitude changes within the window) versus variance (due to the number of samples available in the window for averaging) [4]. Shorter durations reduce bias at the expense of variance, and vice versa. For unwhitened estimates, the best overall window duration was 250 ms. For whitened estimates, it was 500 ms, reflecting that the whitened estimates had lower inherent variance [4]. As with frequency parameters, the upward slope of the contraction provided more reproducible results, presumably because the biomechanics were more repeatable (Table 1). Contraction speed (over the range of speeds studied) had limited influence on the error in the amplitude estimates.

5. Summary

This experimental study performed a cross-comparison of various conventional methods used to estimate MNF, MDF, and amplitude of surface EMG during long-duration, force-varying, constant-posture contractions. Based on these results, the following recommendations can be made when analyzing the cycle-to-cycle behavior of the above EMG parameters when derived from similar cyclic, force-varying, constant-posture contractions: (a) successive comparisons should be aligned to the actual force produced rather than the target force to provide more consistent biomechanics, (b) the window duration should be as long as possible for frequency analysis, while for amplitude analysis the optimum window duration is dependent on the processing technique (500 ms for whitened processors, 250 ms for unwhitened), (c) STFT and TVAR techniques can be used interchangeably (they provide nearly identical results) and seem to provide competent results even though the EMG signal is non-stationary, (d) since frequency variables are influenced by additive background noise, changes in frequency variables as a function of force may be confounded by the relative magnitude of noise with respect to the EMG signal, (e) portions of recordings in which the force is below 20–30% MVC are best avoided due to excessive contamination by additive background noise, (f) spectral noise adjustment (as suggested by Baratta et al. [1]) seems detrimental because the analysis duration is so short (e.g., $\leqslant$500 ms), (g) MNF and MDF are equally reliable when the force is above 20–30% MVC (MDF is most beneficial when the SNR is low), (h) the speed of the contraction can be selected based on physiological considerations, since it has limited influence on the frequency variables, (i) whitened EMG amplitude estimates are preferred, as they provide lower variance, and (j) it may be better to analyze EMG during the rising phase of the contraction, due to improved biomechanical repeatability.

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Edward (Ted) A. Clancy received the B.S. degree from Worcester Polytechnic Institute (WPI), and the S.M. and Ph.D. degrees from Massachusetts Institute of Technology (MIT), all in Electrical Engineering. He has worked in industry for medical instrumentation and analysis companies interested in EMG, EEG, ECG and blood pressure, and the defense industry (aircraft instruments and radar). He is Associate Professor of Electrical and Computer Engineering, and of Biomedical Engineering at WPI. He is interested in signal processing, stochastic estimation and system identification, particularly as applied to problems in medical engineering and human rehabilitation.

Dario Farina graduated summa cum laude in Electronics Engineering from Politecnico di Torino, Torino, Italy, in February 1998. During 1998 he was a Fellow of the Laboratory for Neuromuscular System Engineering in Torino. In 2001 he obtained the Ph.D. degree in Electronics Engineering at Politecnico di Torino and at the Ecole Centrale de Nantes, Nantes, France. In 1999–2004 he taught courses in Electronics and Mathematics at Politecnico di Torino and in 2002–2004 he was Research Assistant Professor at the same University. Currently, he is Associate Professor in Biomedical Engineering at the Faculty of Engineering and Science, Department of Health Science and Technology of Aalborg University. He acts as referee for many scientific international journals and is on the Editorial Board of the Journal of Electromyography and Kinesiology. His main research interests are in the areas of signal processing applied to biomedical signals, modeling of biological systems, and basic and applied physiology of the neuromuscular system. Dr. Farina is a Registered Professional Engineer.

Roberto Merletti graduated in Electronics Engineering from Politecnico di Torino, Italy, and obtained the M.S. and the Ph.D. in Biomedical Engineering from The Ohio State University. Since 1984 he is Associate Professor of Biomedical Instrumentation at the Department of Electronics of Politecnico di Torino. From 1989 to 1994 he was Associate Professor at the Department of Biomedical Engineering of Boston University and Research Associate at the Neuromuscular Research Center of the same University. In 1996 he founded the Laboratory for Neuromuscular System Engineering at Politecnico di Torino, where he is currently Director. He is Coordinator of a project sponsored by the European Community and of a project sponsored by the European Space Agency. His research focuses on detection, processing and interpretation of surface EMG, on electrical stimulation and neuromuscular control.