Quantification of the timing of continuous modulated muscle activity in a repetitive-movement task

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Abstract
The timing of muscle activity is commonly measured in studies of motor control. In repetitive-movement tasks, muscle activity may be continuous, and no defined onset or offset of activity may be measured. This does not imply that no timing of muscle activity occurs. Where activity is continuous, this timing will typically be exhibited by modulation of the amplitude of the signal in specific movement phases. The existence of this electromyographic (EMG) timing is dependent upon the existence of EMG amplitude modulation. This paper investigates this relationship in developing a quantification algorithm of EMG timing in a repetitive-movement task. A frequency domain quantification algorithm involving EMG linear-envelope generation is used. An EMG simulation algorithm is used to test this algorithm and determine the minimal amplitude-modulation threshold for timing detection. At five repetitive-movement speeds (25, 50, 75, 100 and 125 cycles of movement per minute), thresholds between 1.55 and 2.32 times maximal to minimal linear-envelope amplitude are required for reliability of timing detection. Analysis of variance indicates that the robustness of the quantification algorithm was not significantly affected by burst width ($F = 3.69, p = 0.055$) or the underlying input timing parameter ($F = 0.52, p = 0.992$). The phase-lead/lag quantification algorithm represents a useful tool for the analysis motor control via EMG during repetitive-movement tasks.

Keywords: surface electromyography, repetitive-movement, motor control, onset, phase-lead/lag
1. Introduction

The relative timing of muscle activity, as determined from the electromyographic (EMG) signal, is commonly examined in studies of central nervous system (CNS) control of musculature. Differences in timing indicate functional differences between muscles in contributing to a particular task (e.g. Hodges and Richardson (1996)). In many studies, when rapid movement occurs, the onset of muscle activity can be determined by a sudden increase in EMG amplitude above baseline noise. Typically, visual inspection or an automated algorithm is used to quantify the onset of muscle activity (e.g. Hodges and Bui (1996)).

In recent years, however, repetitive-movement tasks have gained wider use in the investigation of CNS control of muscle function (e.g. Belavy et al (2005) and Hodges and Gandevia (2000)). In such movement tasks, the muscles of a proximal body region (e.g. trunk) are of prime interest, but repetitive movement of a distal segment (e.g. arm or leg) is used as a stimulus for proximal muscle activity. Surface EMG signals of the proximal musculature from these repetitive-movement tasks typically exhibit continual activity. Although there may be no distinct onset or offset of muscle activity, periodic modulation of EMG amplitude may occur during consistent phases of movement (see figure 1(C)).

Similar to the onset of muscle activity, the timing of EMG amplitude modulation (phase-lead/lag) during repetitive movement is relevant for the study of motor control. It could, for example, imply the phase of movement at which the CNS increases the contribution of a particular muscle. In the proximal musculature during repetitive-movement tasks, it may reflect when increased contribution to the assistance in movement production, the maintenance of posture, or to joint stabilization occurs. It is therefore relevant to quantify this relative phase-lead/lag.

Two studies have been identified in the literature to date that quantified phase-lead/lag. In both studies, EMG signals were first processed to produce a profile (or linear envelope) of EMG. In one study (Ivanenko et al 2004), a cross-correlation function between linear envelopes was calculated. The peak (positive) cross-correlation value and its corresponding time lag determined the phase-lead/lag between the two signals. In the second study (Ting et al 1999) the angular-displacement signal from the repetitive-movement task (pedalling) and the linear envelopes extracted from leg muscle EMG signals were partitioned into 16 phases. To determine phase-lead/lag between two signals, Pearson’s product moment correlation coefficient was calculated for each of the 16 phases. The movement phase with the maximal correlation coefficient value was then determined to be the phase-lead/lag.

In each of these studies, muscles of the lower limb were investigated, either during walking (Ivanenko et al 2004) or pedalling (Ting et al 1999). Because of the biomechanical constraints of these tasks, it can be expected that the lower limb muscles exhibit distinct on- and off-phases of EMG activity. Whilst suited to the analysis of EMG signals from muscles involved in movement production, the algorithms used in these studies may not be applicable to the EMG signals considered here: when EMG activity is continuous, but no amplitude modulation occurs (i.e. the EMG is ‘tonic’, such as seen in figure 1(A)), it is still mathematically possible to find a maximal cross-correlation value or correlation coefficient. The resulting phase-lead/lag would however be spurious. Tonic EMG exhibits, by virtue, no periodic ‘timing’ in the changes in its amplitude. When periodic EMG amplitude modulation increases, however, the phase-lead/lag detection algorithm would, at a certain point, become reliable.

The aim of the current work is to quantify at what levels of EMG amplitude modulation during a repetitive-movement task, the phase-lead/lag measure becomes reliable. In
investigating this relationship, we also consider the robustness of a frequency domain phase-lead/lag quantification algorithm.

2. Materials and methods

2.1. Repetitive-movement EMG simulation algorithm

In order to test the reliability of a phase-lead/lag quantification algorithm, it is necessary to implement an algorithm that simulates EMG signals with systematic variation of EMG amplitude modulation and phase-lead/lag. We have developed an appropriate algorithm in prior work (Belavý et al. 2006) to simulate isometric lumbo-pelvic muscle activity, as measured with surface EMG, during repetitive movement of a limb (see for example Belavy et al. (2005) and Hodges et al. (2001)). This cyclic/repetitive input necessitates periodic increases in lumbo-pelvic muscle activity (amplitude modulation) to counteract the moment generated by limb movement.

The simulation algorithm (figure 1) uses two separate signals to generate the final EMG signal: (1) a ‘tonic’ (zero amplitude modulation) EMG signal collected from the biceps brachii of subjects performing an isometric contraction (duration: 10 s; sample rate:
2000 Hz; Butterworth band-pass filter: 20–500 Hz) and (2) a synthesized ‘modulation signal’ (2000 Hz, 10 s duration) based upon a half-wave rectified sinusoid with the following parameters:

- Amplitude-modulation index (as a ratio of the desired peak burst EMG amplitude to the underlying tonic activity (input burst-to-tonic ratio, BTRinput)): range 1–14.5 in increments of 0.5.
- Repetitive-movement speed (periodicity of bursts of muscle activity): 25, 50, 75, 100 or 125 cycles per minute (cyc min$^{-1}$) (corresponding to periods of: 2.4, 1.2, 0.8, 0.6 or 0.48 s, assuming one burst of activity per movement cycle).
- Burst width: from 29% to 92% of movement cycle length, in 3% increments.
- Phase-lead/lag (PHZinput): between 0° and 360° at increments of 10°.

The modulation signal and tonic EMG signal are then multiplied point-wise to yield the final amplitude-modulated EMG signal. A sinusoidal (amplitude range −1 to 1) signal of 25, 50, 75, 100 or 125 cyc min$^{-1}$ is also outputted to represent the angular displacement of the limb (as may be measured by an electrogoniometer; Belavý et al 2005). The parameters that characterize the modulation signal explain between 91.9% and 96.2% of the variance of EMG linear-envelope signals of lumbo-pelvic muscles acting during a repetitive limb movement task (Belavý et al 2006). All algorithms described herein have been implemented in the Labview 6.1 programming environment (National Instruments, Texas).

2.2. Phase-lead/lag quantification algorithm

The phase-lead/lag algorithm aims to quantify timing differences of amplitude modulation between the simulated EMG and angular-displacement signals. A frequency domain approach is used. Whilst such analyses would ideally be conducted on an infinite series, human subjects undertaking a repetitive-movement task cannot maintain perfect speed and movement amplitude accuracy for indefinite periods. After initial processing of the entire EMG signal, the algorithm analyses timing differences in a discrete subsection of both signals (figure 2):

(a) Extraction of a linear envelope from the entire 10 s simulated EMG signal: 20–500 Hz, tenth-order Butterworth band-pass filter is first applied. The signal is then full-wave rectified and then low pass filtered using a 10 Hz tenth-order digital Bessel filter (Belavý et al 2006).

(b) Partitioning of the angular-displacement signal and EMG linear envelope into discrete subsections:

(i) In simulated EMG data sets: random selection of three consecutive movement cycles, beginning at a minimum (amplitude: −1), of the angular-displacement signal.
(ii) In EMG data sets collected from subjects during a movement task we use the following criteria: three consecutive movement cycles, beginning at a minimum, during which each movement cycle’s speed is within ±5 cyc min$^{-1}$ of the target speed, and the maxima and minima are within ±4° of their respective targets (Belavý et al 2006). These criteria may differ depending on the movement task employed.

(c) Calculation of the amplitude spectrum of the angular-displacement signal and determination of movement frequency (frequency of the peak positive value).
(d) Calculation of the phase spectra (in radians) of the linear-envelope and angular-displacement signals.
Figure 2. Phase-lead/lag quantification algorithm. (A) The subsets of synthesized angular-displacement and linear-envelope signals have been rescaled and superimposed to allow visual comparison of relative timing differences (the linear-envelope subset has been extracted from the high \( BTR_{input} \) EMG signal in figure 1(C)), the amplitude spectrum of the angular-displacement signal is subsequently generated (not shown) and the frequency at its peak positive value calculated (in this case 1.66 Hz); (B) phase spectra of the linear-envelope (triangles) and angular-displacement (circles) subsets are then calculated. The difference between the two phase spectra at the detected movement frequency (1.66 Hz) is coerced to between \(-\pi\) and \(\pi\) (in the above example \( PHZ_{output} = -2.08 \text{ rad, } -118.9^\circ \)).

(c) Subtraction of the value in the linear-envelope phase spectrum at the movement frequency from the same value in the angular-displacement signal phase spectrum.

(f) Coercion of this phase difference to between \(\pi\) and \(-\pi\) and converted to degrees.

This final result is then the phase-lead/lag between the EMG linear-envelope and the angular-displacement signal \( PHZ_{output} \). For each increment of \( BTR_{input} \) in the EMG simulation algorithm, Pearson’s correlation coefficient \( r \) was calculated between the \( PHZ_{input} \) and \( PHZ_{output} \) values (figure 3). When \( |r| \) was greater than 0.95, the detected phase-lead/lag \( PHZ_{output} \) was assumed to be reliable.

2.3. Further processing of the simulated EMG signal

In the simulated EMG signal, the amount of amplitude modulation \( BTR_{input} \) is known. However, in EMG signals from real-world repetitive-movement tasks, this variable is unknown and must be estimated. Therefore, in addition to calculating the phase-lead/lag of the EMG linear envelope \( PHZ_{output} \), its amplitude modulation is also quantified. The following algorithm is used (see Belavý et al (2006) for further details):
Figure 3. Analysis of reliability of PHZoutput. At low levels of BTRinput (left of surface) the relationship between PHZinput and PHZoutput breaks down. If Pearson’s correlation coefficient (r) between PHZinput and PHZoutput is >0.95 at a given level of BTRinput, PHZoutput is taken to be reliable.

(a) Detection of peaks and valleys in the linear-envelope subset (generated in step b of the phase-lead/lag quantification algorithm) using quadratic least-squares fit.
(b) Calculation of the median peak and median valley amplitude.
(c) Calculation of BTRoutput: median peak value divided by median valley value.

BTRoutput is essentially the amplitude-modulation index plus ‘1’. The values of BTRoutput for which the correlation between PHZinput and PHZoutput values is unreliable (−0.95 ≥ r ≤ 0.95) represent amplitude-modulation levels for which a phase-lead/lag cannot be reliably estimated (BTR0). This data set was then used for statistical analyses.

2.4. Statistical analysis

Statistical analysis of the BTR0 data set first aimed to determine what factors affected the robustness of the algorithm. Linear mixed-effects models (Pinheiro and Bates 2000) were used to examine the influence of input repetitive-movement speed, burst width (duty cycle of the modulation signal) and also PHZinput. A log transformation of the BTR0 data set was used to approximate normality and allowances were made for heterogeneity of variance across movement speed. An α level of 0.05 was taken for significance. The ‘R’ statistical environment (version 2.1.1, www.r-project.org) was used for these analyses.

Further analysis determined BTRoutput thresholds for reliability of the PHZoutput value. As a ratio of two positive numbers, the distribution of BTRoutput is positively skewed. Thus, BTRoutput threshold values were calculated as the third quartile plus 1.5 times the inter-quartile range of the BTR0 data set.
Table 1. Threshold values of detected amplitude modulation (BTRoutput) for reliability of detected phase-lead/lag (PHZoutput) at each movement speed (25, 50, 75, 100 and 125 cycles of movement per minute (cyc min\(^{-1}\)).

<table>
<thead>
<tr>
<th>Movement speed (cyc min(^{-1}))</th>
<th>BTRoutput</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>1.558</td>
</tr>
<tr>
<td>50</td>
<td>1.920</td>
</tr>
<tr>
<td>75</td>
<td>2.011</td>
</tr>
<tr>
<td>100</td>
<td>2.129</td>
</tr>
<tr>
<td>125</td>
<td>2.326</td>
</tr>
</tbody>
</table>

3. Results

Figures 2 and 3 depict outputs from the phase-lead/lag quantification algorithm. As can be seen in figure 3, the algorithm is quite sensitive to alterations in PHZinput once sufficient amplitude modulation (BTRinput) is present in the EMG signal.

Analysis of variance of the BTR\(_0\) data set indicated a significant main effect for repetitive-movement speed (\(F = 523.70\), \(p < 0.001\)). No significant main effects existed for PHZinput (\(F = 0.52\), \(p = 0.992\)), burst width (\(F = 3.69\), \(p = 0.055\)) or a burst width by movement-speed interaction (\(F = 0.97\), \(p = 0.423\)). The mean BTR\(_0\) values at 50, 75, 100 and 125 cyc min\(^{-1}\) movement speeds were all significantly higher than at the 25 speed (\(T = 23.52, 24.17, 27.16\) and 32.30 respectively, all \(p < 0.001\)). As movement speed significantly influenced the robustness of the algorithm, BTRoutput thresholds were calculated for each speed (table 1).

To allow extrapolation of thresholds at other movement speeds, an exponential function was fitted to the threshold values in table 1. The resultant equation: \(y = 1.50 \times e^{0.0036x}\) (where \(x\) is the movement speed in cyc min\(^{-1}\)) had an \(R^2\) of 0.91.

4. Discussion

The phase-lead/lag quantification algorithm presented here represents a new tool for the analysis of EMG signals from repetitive-movement tasks. The predominant application of this algorithm is in the field of motor control research. Prior research has shown the importance of appropriate muscle activation timing (relative to a fixed event, such as arm movement) in movement, the control of posture and joint stabilization (e.g. Hodges and Richardson (1996)). To date, however, this has typically been limited to studies of activation ‘onset’ relative to an internal or external perturbation. Utilizing the algorithm presented in the current work, the study of motor control can be expanded to the timing of muscle activation in a cyclic, or repetitive, movement tasks. Importantly, we have presented amplitude-modulation threshold levels to show when such quantification is reliable.

Two main limitations of the current work exist however. Firstly, the amplitude-modulation thresholds were determined for specific speeds of repetitive movement, not for all possible speeds. It is, however, possible to extrapolate BTRoutput threshold values at other movement speeds. We fitted an exponential function to allow this extrapolation.

The second limitation is that PHZoutput represents the phase-lead/lag between the EMG linear envelope, not the EMG signal itself. Linear-envelope filtering using a Bessel filter produces a consistent phase shift across all frequencies. This is a specific limitation, in
addition to electromechanical delay, on drawing inferences on actual onset of the mechanical
effect of muscle activity. This limitation is, however, common also in motor control studies
that quantify muscle activation onset (Hodges and Bui 1996). Inferences on motor control
drawn from the current algorithm would, such as in studies of activation onset (see for example
Hodges and Richardson (1996)), be based upon timing differences between muscles and/or
subject groups, rather than on time of onset of muscle force generation.

The phase-lead/lag quantification algorithm is, however, quite robust. The duty cycle
(burst width) of the input EMG does not significantly influence the algorithm’s ability to
detect a phase-lead/lag between the angular-displacement signal and the EMG linear envelope.
Also, the underlying phase-lead/lag (PHZinpu) does not affect the reliability of quantification
algorithm. Movement speed did affect the reliability of phase-lead/lag detection, however,
presumably due to the influence of data length (higher thresholds at shorter data lengths). For
this reason we calculated BTRoutput values for PHZoutput reliability at these different movement
speeds.

5. Conclusions

In summary, we have evaluated an algorithm that quantifies the relative timing (phase-lead/lag)
between EMG linear-envelope and angular-displacement signal. The robustness of this
algorithm was significantly affected only by movement speed. Minimum threshold values
of linear envelope amplitude modulation at discrete movement speeds were calculated and at
different movement speeds, threshold values can be extrapolated from the data presented here.
The algorithm we have presented is a tool useful in analysis of surface EMG signals from
repetitive-movement tasks as part of the assessment of CNS motor control of the musculature.

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