

Wavelet Frequency-Temporal Relative Phase Pattern Analysis for Intermuscular Synchronization of Dynamic Surface EMG Signals

Calvin W. Y. Chan, *Member, IEEE*, Sivan Almosnino, and Evelyn L. Morin, *Senior Member, IEEE*

Abstract—Cross-correlation is often used as the primary technique to compare two biological signals. Cross-correlation is an effective means to measure the synchronization of two signals assuming the relative phases of all frequencies are distributed linearly, that is, a group delay. The group delay assumption imposes an unfavorable restriction on signals with varying relative phase correlation at different frequencies. The traditional Fourier technique provides phase information for each frequency component, but it is not suitable for biological signals with non-stationary statistics. The application of a wavelet based phase analysis technique is discussed in this study. The frequency decomposition and temporally localized nature of the wavelet transform provides localized phase-frequency information for two signals. The merits and weaknesses of using the wavelet relative phase pattern for determining the synchronization of surface electromyographic signals from two muscle sites is discussed.

I. INTRODUCTION

THE correlation of two time varying signals is of interest in the field of biological signal analysis. A simple and well-established method for analyzing the correlation between two time series involves computing the cross-correlation function. In the realm of biomechanical research, cross correlation has been used for quantifying temporal similarity between pairs of electromyographic (EMG) signals [1]-[3], and to assess joint kinematic timing differences [4]. The use of cross-correlation to measure similarities between two signals suffers from two major problems: (1) cross-correlation analysis is based on an underlying assumption that all the frequency components of the two time series are correlated with a group phase difference, that is, a linear phase difference with respect to the change of frequency, and (2) cross-correlation provides insights into the correlation of the signal in an average manner; time localized correlation occurs within a certain time interval and is difficult to detect and extract. The former problem could be addressed by computing the relative phase difference of the cross-spectral density between the two signals. Comparing

the phase of each frequency component of the two signals, relative phase shifts at the different frequencies can be identified. The problem of time locality can be addressed by computing the cross-spectral density over predetermined interval lengths, using the short-time Fourier transform (STFT), or by using the wavelet transform to investigate the correlation relationship at different resolutions. STFT suffers from the following problems: (1) STFT requires prior knowledge of the correlation duration interval to select the appropriate window length and (2) the selected window length is usually not optimized according to the Heisenberg uncertainty criterion to reveal the time localized behavior of the signal on the time-frequency plane. A wavelet transform approach was chosen for this study. In contrast to De Michele *et al.*'s [5] approach, instead of analyzing the wavelet cross-spectral energy between EMG signals, this study focuses on the relative phase information between the signal pair. This work explores the wavelet frequency-temporal relative phase pattern (WFT-RPP) as a qualitative tool for assessing intermuscular synchronization between surface EMG (sEMG) signals measured at two different muscle sites from a top-level perspective. In this study, the details of WFT-RPP implementation and the results of applying the technique on sEMG signals recorded from pairs of muscles during dynamic contractions are discussed.

II. METHODS

A. Experimental Setup

The experiment was conducted at the Motor Performance Laboratory of Queen's University. Eight male subjects aged 20 to 25 years old, with no history of upper extremity injury, participated in the study, after providing informed consent. sEMG signals were recorded from 8 muscle sites on the dominant arm including: anterior, medial, and posterior deltoid, biceps brachii, long head and lateral head of the triceps brachii, forearm extensor carpi radialis, and forearm flexor carpi radialis. The electrodes were placed according to the SENIAM electrode placement guideline 2010 [6]. sEMG signals were detected using bipolar, pre-gelled Ag-Ag/Cl electrodes with an inner diameter of 10mm and a fixed inter electrode distance of 20 mm (Bortec Biomedical Ltd., Calgary, Alberta, CA). A common reference electrode was placed on the most prominent part of the right olecranon (pre-gelled, Ag-Ag/Cl, 10mm inner diameter, Meditrace Model 135, Kendall, MA, USA). The sEMG electrodes were interfaced with a Bortec AMT-8 amplifier (frequency response 10 Hz to 1 kHz, common mode rejection ratio

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C. W. Y. Chan is with the Electrical and Computer Engineering Department, Queen's University, Kingston, Ontario, K7L 3N6 Canada (phone: 613-533-6000 ext.77956; fax: 613-533-6615; e-mail: w.y.calvin.chan@queensu.ca).

S. Almosnino is with the School of Kinesiology and Health Studies, Queen's University Kingston, Ontario, K7L 3N6 Canada (e-mail: sivan.almosnino@queensu.ca).

E. L. Morin is with the Electrical and Computer Engineering Department, Queen's University, Kingston, Ontario, K7L 3N6 Canada (e-mail: evelyn.morin@queensu.ca).

>115 dB at 60 Hz, input impedance > 1 GΩ, gain level 2000). Signals were sampled at 2000 Hz using custom software written in Labview™ version 8.6 (National Instruments Inc., Austin, TX, USA). For task performance, each participant was seated on a Biodex Isokinetic Dynamometer (BID) with the upper body restrained. The participant was instructed to grasp a handle attached to an adjustable robotic rail on the BID and perform three sets of push and pull tasks using the dominant arm. The motion was constrained horizontally to be parallel to the transverse plane and perpendicular to the coronal plane at a constant angular speed of 20° per second. The subject performed three push and pull tasks at 4 different self-perceived effort levels (40%, 60%, 80%, and 100% maximum effort). This was followed by a fatigue study in which the participant was instructed to continuously perform the push-and-pull task at full effort (100%) until failure. This study was approved by the Research Ethics Board, Queen's University.

B. Data Collection and Data Preprocessing

The recorded EMG data were processed offline with a 10th order, linear phase, digital FIR least square low-pass filter with pass band frequency at $f_{\text{pass}} = 500$ Hz and stop band frequency $f_{\text{stop}} = 600$ Hz to prevent down sample aliasing. Following the low-pass filter, the signal was down sampled from the original sampling frequency of $f_s = 2$ kHz to $f_s = 1$ kHz to reduce computational complexity. It was expected that the repeated push and pull motion would create a periodic artifact on the EMG data at the lower frequency band. These frequency components can introduce noise at higher frequencies due to spectral leakage caused by the use of non-orthogonal wavelet bases in the continuous wavelet transform (CWT). To eliminate the potential interference of the lower frequency artifact, the EMG data were further filtered with 150th order, linear phase, digital FIR least square high-pass filter with stop band frequency at $f_{\text{stop}} = 2$ Hz and pass band frequency at $f_{\text{pass}} = 20$ Hz.

C. Relative Phase and Wavelet Semblance Analysis

To evaluate the phase-frequency relationship of two signals, the continuous wavelet transform (CWT) is used. The complex Morlet wavelet is used as the wavelet transformation basis in this study. The complex Morlet wavelet can be viewed as a time constrained equivalent of the complex sinusoidal function amplitude modulated by a Gaussian function. The Morlet wavelet can be computed using:

$$\Psi(x) = \frac{1}{\pi f_b} e^{2j\pi f_c x} e^{-\left(\frac{x^2}{f_b}\right)} \quad (1)$$

where f_b controls the bandwidth and f_c controls the center frequency of the wavelet. The Morlet wavelet is shown in Fig. 1. The relative phase between two signals can be

computed by evaluating the phase angle between the wavelet components of the signals in the complex domain. The frequency-temporal localized property of the wavelet transform can provide insights into the instantaneous synchronization of two separate signals. The relative phase of the two signals is plotted on the time-frequency plane to generate the WFT-RPP plot.

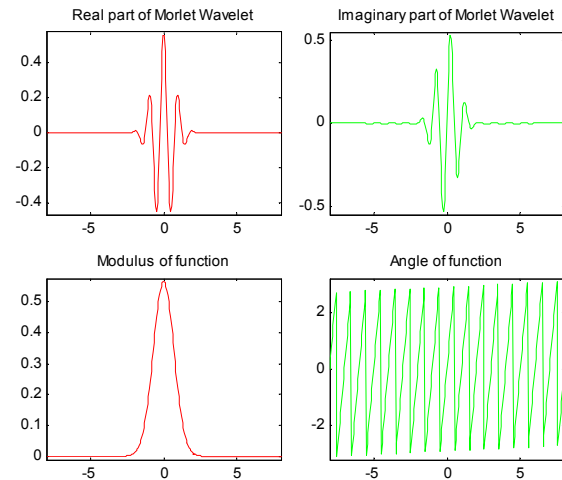


Fig. 1. Complex Morlet wavelet, $f_b=1, f_c=1$ (cmor1-1).

The cosine of the wavelet relative phase, namely the semblance analysis, was introduced as an effective tool to suppress noise while also suppressing the amplitude information [7]. In this study, the performance of WFT-RPP and the semblance plot is compared.

D. Testing the WFT-RPP Algorithm

The WFT-RPP of two signals each containing three sinusoidal components (30 Hz, 50 Hz, 80 Hz) is examined. All frequency components are summed together to produce the simulated input signal, where the relative phase between each frequency component changes every second over a duration of 3 seconds. The purpose of this analysis is to investigate the effects of random noise, wavelet bandwidth, and the wavelet energy leakage on WFT-RPP.

III. EXPERIMENTAL RESULTS

A. WFT-RPP of Mixed Sinusoidal Waves

The relative phase plot is computed with respect to the center frequency of the wavelet, namely the wavelet pseudo-frequency. The inversely proportional relationship between the wavelet scale to the pseudo-frequency scale shows very fine detail at the lower frequency region (see Figure 2). The results of the WFT-RPP analysis of the mixed sinusoidal waves are shown in Fig. 2. It is worth noting that the CWT uses a set of non-orthogonal wavelet bases causing energy leakage to nearby frequencies. This energy leakage introduces information redundancy between the wavelet bases which poses a problem in precisely determining the exact frequency of the signal contents. Further, from the

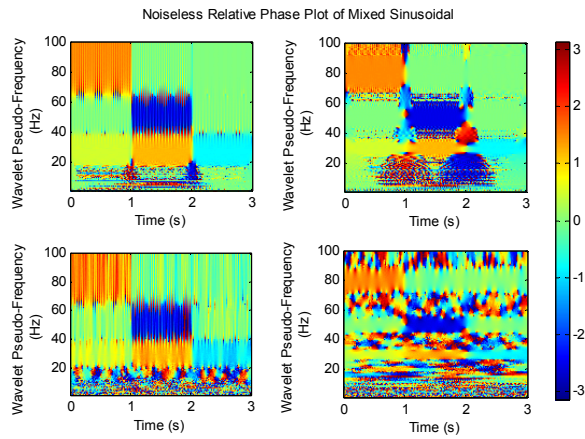


Fig. 2. WFT-RPP of two mixed sinusoidal signals in comparison: $f = 30$ Hz, 50 Hz, 80 Hz (i) (upper left) Noiseless cmor1-1, (ii) (upper right) Noiseless cmor20-1, (iii) (lower left) SNR=3dB cmor1-1, (iv) (lower right) SNR = 3 dB cmor20-1.

noiseless case it is observed that the WFT-RPP plot fails to provide information at frequency bands with little or no signal content, potentially providing misleading phase information.

B. WFT-RPP versus Semblance Analysis

A comparison between the WFT-RPP plot and a semblance plot for recorded sEMG signals is shown in Fig. 3. The relative-phase lead and lag features are combined in the semblance plot and produce less feature information. The arrows above each plot represent the push-pull phases of the movement.

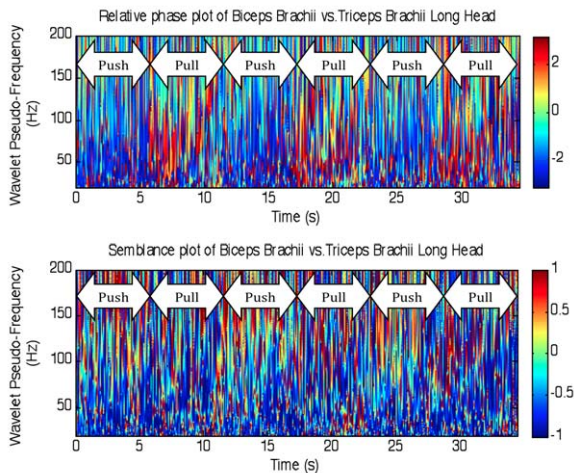


Fig. 3. Subject 7, biceps brachii sEMG versus triceps brachii sEMG (i) (above) WFT-RPP (ii) (below) Semblance analysis.

C. Contraction Level and Cross-subject Comparison

Recorded sEMG is known to have a stochastic nature. A noiseless synchronization pattern, that is, a large area with small relative phase change on the frequency-temporal plane, is not to be expected. Most statistical processing methods cannot be used due to the non-stationary nature of the EMG signal during dynamic flexion and contraction of muscles. The WFT-RPP plots for two subjects performing the push and pull task at various effort levels measured relative to

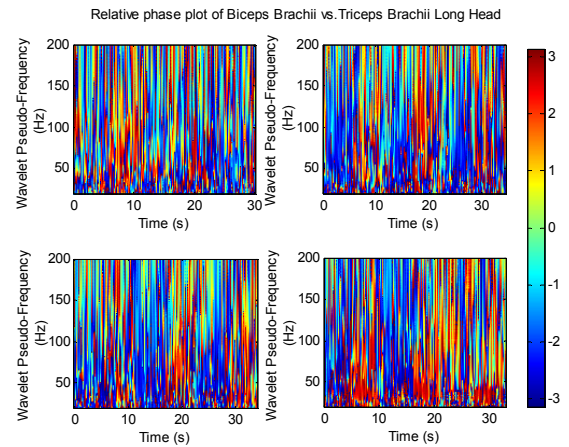


Fig. 4. WFT-RPP of subject 7 at different effort levels for sEMG of biceps brachii versus triceps brachii (i) (upper left) 40% MVC (ii) (upper right) 60% MVC (iii) (lower left) 80% MVC (iv) (lower right) 100% MVC.

maximum voluntary contraction (MVC) level are shown in Fig. 4. The results show that the WFT-RPP patterns at different effort levels are similar. It is observed that the pattern emerges as the statistical noise decreases with respect to the increase of the effort level and similar results were observed in all subjects. The synchronization patterns are generally observed below 150 Hz. The WFT-RPP plot of 4 subjects with the same testing protocol is shown in Fig. 5. The WFT-RPP plots for all subjects appear to have repetitive activity at the same frequency range with a circular phase shift (the phase is rotated by 2π rad). For subject 4 the WFT-RPP pattern appears different at the third push and pull cycle, which may indicate that a different muscle strategy is employed to perform the task. Similar results were obtained for the other 4 subjects.

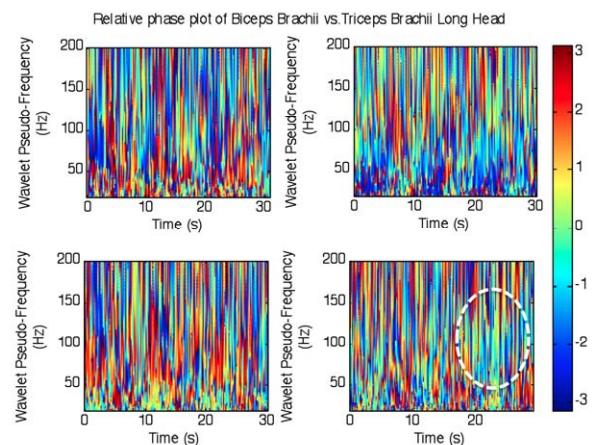


Fig. 5. WFT-RPP of subject 1-4 at 80% MVC for sEMG of biceps brachii versus triceps brachii (i) (upper left) Subject 1 (ii) (upper right) Subject 2 (iii) (lower left) Subject 3 (iv) (lower right) Subject 4.

IV. DISCUSSION

A. Nature of WFT-RPP and WFT-RPP on sEMG

In the analysis of the mixed sinusoidal signals, the changing relative phase of the frequency components was

detected by WFT-RPP, however there is a frequency spread in the time-frequency plane. The problem of determining the exact frequency components is directly related to the Heisenberg uncertainty principle - as the bandwidths of the wavelet bases increases, a temporal spread occurs in exchange for a more precise frequency locality. A higher bandwidth wavelet basis can be chosen, but only at the cost of reducing the temporal resolution. The presence of broadband noise was found to help localize the frequency components by filling in intermediate frequencies in the time-frequency plane with random phase values as shown in Fig. 3 (iv). In the WFT-RPP for sEMG pairs, it was observed that synchronization is restricted to a lower frequency range (frequencies below 200Hz). This might be due to (1) the channel distortion of the EMG signals passing through the biological tissue, which prevents detection of high frequency synchronization, (2) high frequency synchronization varies too quickly under the nonstationary statistics due to dynamic contraction and is indistinguishable from the noise or (3) there is limited signal content present beyond this frequency range. Linear phase FIR filters are used in this study for data preprocessing. It is worth noting that a nonlinear phase filter could be used without affecting the WFT-RPP results. The pairwise comparison produces the same result when each frequency component of both sEMG channels experiences the same phase shift, therefore, the relative-phase between the frequency components is not changed.

B. Electrode Position and sEMG Spatial Delay

The relative group delay of two sEMG channels is highly dependent on the electrode locations with respect to the muscle innervation zones. The relative physical distances introduce a relative propagation delay, thereby altering the relative phase of the signals. Assuming all frequency components propagate at the same velocity, the relative electrode placement could produce a circular phase shift pattern (a shift from $-\pi$ to π rad) for the same muscle control signal. This circular phase shift results in a different temporal shift with respect to different frequency components. Further, the relative position of the electrode and the innervation zone of a muscle changes during dynamic contraction thus introducing an additional layer of complexity to the signal. The relative positioning of the electrode and the change of relative position with respect to the innervation zone poses the two major limitations for this technique.

C. WFT-RPP versus Semblance Analysis

In Fourier analysis, the transform bases are periodic sinusoidal functions. The relative phase in accordance to each frequency component of two signals is the angular phase difference between these components. The relative phase is a rotational parameter mapping from $-\pi > \theta > \pi$ to $-\pi > \theta > \pi$ where θ corresponds to the phase lead or lag of the periodic self-repeating sinusoidal basis functions. The relative phase can correspond to both a phase lead and phase lag. For

example, a phase lead of $\theta = 3\pi/4$ is equivalent to a phase lag of $\theta = -5\pi/4$. Therefore, the phase lead and phase lag provide little information while the overall relative phase pattern is of interest.

In this study, non-periodic wavelet functions were used to determine the instantaneous relative phase on the time-frequency plane. The relative phase lead and lag is therefore limited to the duration of the wavelet bases. The indistinguishable phase leading and lagging phenomenon in Fourier analysis is not present in the wavelet case. The energy of each wavelet basis concentrates in a temporal region with respect to its scale parameter. Therefore, the relative lead or lag of the two signals can be determined. Cooper and Cowan [7] suggested the use of the cosine function to improve the noise susceptibility, namely the semblance plot. This approach eliminates the lead-lag information between the two signals due to the 2-to-1 mapping of the cosine function between $-\pi$ to π . In sEMG synchronization analysis, we are interested in the change of the instantaneous relative phase in the frequency-temporal plane instead of the exact relative phase due to the relative spatial delay mentioned in the previous section. Hence, the nonlinear mapping of the cosine function is inappropriate for the purpose of analyzing muscle pair sEMG synchronization.

V. CONCLUSION

The WFT-RPP effectively expresses the phase relationship of band restricted low amplitude components of the sEMG which is undetectable in traditional correlation analysis. The WFT-RPP can potentially be applied to clinical diagnosis or as a feature extraction technique for force estimation. However, at low muscle contraction levels, the synchronization pattern is buried under statistical noise. This problem can potentially be overcome by taking a statistical average using each dynamic task cycle as a sample from a stochastic process. As well, the visual readability of the WFT-RPP plot can be improved by filtering with a low-pass image filter to eliminate the statistical noise.

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