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Time-varying delay estimators for measuring muscle fiber conduction velocity from the surface electromyogram

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A B S T R A C T

Muscle fiber conduction velocity (MFCV) can be measured by estimating the time delay between surface EMG signals recorded by electrodes aligned with the fiber direction. In the case of dynamic contractions, the EMG signal is highly non-stationary and the time delay between recording sites may vary rapidly over time. Thus, the processing methods usually applied in the case of static contractions do not hold anymore and the delay estimation requires processing techniques that are adapted to non-stationary conditions. The current paper investigates several methods based on time-frequency approaches or adaptive filtering in order to solve the time-varying delay estimation problem. These approaches are theoretically analyzed and compared by Monte–Carlo simulations in order to determine if their performance is sufficient for practical applications. Moreover, results obtained on experimental signals recorded during cycling from the *vastus medialis* muscle are also shown. The study presents for the first time a set of approaches for instantaneous delay estimation from two-channels EMG signals.

1. Introduction

The estimation of time delays is an important topic in several biomedical applications. For example, muscle fiber conduction velocity (MFCV) can be measured by estimating the time delay between surface EMG signals recorded by electrodes aligned with the fiber direction (for a recent review, see [1]). The measure of MFCV has been shown to be relevant in the diagnosis of pathologies [2], fatigue [3] and in the detection of neuromuscular system adjustments due to exercise [4]. A major objective of these studies is to understand the motor unit (MU) recruitment strategies of the motor control. Most of these studies were conducted during static activity. However, it has been demonstrated that the MU recruitment was task-dependent [5] suggesting that this recruitment was different between dynamic and static contractions. Any results extrapolation from static to dynamic studies remains *de facto* speculative. Therefore, there is a real necessity to estimate the MFCV during dynamic activities which compose a main part of common activities (walking, running, cycling or jumping). The most commonly applied methods for estimating MFCV are based on the assumption of signal stationarity and constant delay within the processing interval, which is usually in the range 250 ms–1 s [6]. This assumption is valid for static contractions of moderate force but not during dynamic tasks or contractions consisting in rapid changes in the force expressed [7]. Indeed, in dynamic conditions, the EMG signal is highly non-stationary and the time delay between recording sites may vary rapidly over time due to recruitment and/or derecruitment of motor units with different MFCVs. In order to properly analyze the MFCV evolutions during these tasks, it is necessary to develop processing techniques that are adapted to non-stationary conditions. In the non-stationary case, the MFCV estimation is a time-varying delay estimation problem. Only few previous studies addressed the problem of estimating time delays from surface EMG signals recorded during dynamic tasks. Farina et al. [8] adapted a maximum likelihood estimator to short analysis intervals for its use in dynamic contractions, however the resulting approach does not provide an instantaneous delay estimation. Non-stationarity implies time-varying statistics of the data. Consequently, the analysis methods should provide local estimates. Time-frequency representations (TFR) and adaptive filtering techniques are among those approaches which are suited for non-stationary signals analyses. For example, time-varying delay estimators have been developed for turbulent flow analysis based on the wavelet cross-power spectrum [9]. Adaptive filtering techniques for time-varying delay estimation have also been theoretically developed and investigated in terms of convergence

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rates and accuracy [10,11]. In this paper, we address the problem of estimating the time-varying delay between two EMG signals with the purpose of measuring MFCV in non-static conditions. For that, we propose to develop a set of delay estimation methods based on TFRs that are the most original part of this study. These methods are theoretically analyzed and modified to be adjusted to the EMG signal characteristics. In order to evaluate the quality of the methods proposed, an alternative method based on an adaptive filtering procedure already used for time-varying delay measure [12] is presented and tested. The different approaches are compared through Monte–Carlo simulations in order to classify them and to determine if their performance statistics are sufficient for practical applications. Moreover, we confront these methods to experimental data collected in dynamic exercise conditions in order to test the ability of the methods to track the MFCV in the range of physiological acceptable values. The study presents for the first time a set of approaches for instantaneous delay estimation from EMG signals.

2. Methods

2.1. Problem definition

We adopt a surface EMG model that allows the generation of signals with a well defined time-varying delay. The EMG signal is the sum of motor unit action potentials and can be considered as a Gaussian process when a sufficient number of contributions are present [13]. The power spectral density of this signal can be modeled by an analytical parameterized shape [14]. Moreover, the signal is contaminated by instrumentation and recording noise sources, which are uncorrelated to the EMG. Thus, the recorded signal can be expressed as an EMG component with Gaussian distribution and with a pre-defined spectral shape, summed to an uncorrelated white noise component.

In this study, we will consider a simple two-channels model:

$$\begin{cases} x_1(t) = s(t) + w_1(t) & 0 \le t \le T \\ x_2(t) = s(t-\theta(t)) + w_2(t) & 0 \le t \le T \end{cases} \quad (1)$$

where $\theta(t)$ is the time-varying delay between the first and the second channel. The $w_1(t)$ and $w_2(t)$ are white noises which are independent between each other and with respect to the signal $s(t)$. T is the observation duration.

The following derivations will consider continuous variables for time t and frequency f. For the final computer application, the variables will be respectively digitized in variables n and k.

2.2. Time-frequency representations (TFR)

Among the TFRs, we will focus on the bilinear (also called quadratic) transforms. These transformations allow the definition of cross-transforms between two signal sources. Among the TFR, the Cohen's class gathers the set of energetical TFR that are invariant by translation in time and frequency [15]. Regarding the stochastic nature of the data, we define $P_{x_1x_2}(t,f)$ the sliding cross power spectral density (SxPSD) between the channel $x_1(t)$ and the next channel $x_2(t)$ as the averaging of the windowed interspectrum $S_{x_1x_2}(t,f)$ as:

$$P_{x_1x_2}(t,f) = \mathbf{E}\left\{S_{x_1x_2}(t,f)\right\} \quad (2)$$

or

$$P_{x_1x_2}(t,f) = \mathbf{E}\left\{X_{x_1}(t,f)X^*_{x_2}(t,f)\right\} \quad (3)$$

where $X_{x_k}(t,f) = \int_{-\infty}^{+\infty} x_k(\tau)h(\tau-t)e^{-j2\pi f\tau}d\tau$ is the Fourier transform of the signal $x_k(t)$ windowed by the function $h(t)$ and $\mathbf{E}$ is the mathematical expectation. When $x_1(t) = x_2(t)$, this equation defines the sliding power spectral density (SPSD). According to the model of Eq. (1), we obtain the following decomposition:

$$P_{x_1x_2}(t,f) = P_{s\tilde{s}}(t,f) + P_{sw_2}(t,f) + P_{w_1\tilde{s}}(t,f) + P_{w_1w_2}(t,f) \quad (4)$$

where $\tilde{s}(t) = s(t-\theta(t))$. Since the noise components $w_1(t)$ and $w_2(t)$ are centered, independent from $s(t)$ and from each other, the last three terms in Eq. (4) are zero. The remaining expression is thus:

$$P_{x_1x_2}(t,f) = \mathbf{E}\left\{X_s(t,f)X^*_{\tilde{s}}(t,f)\right\} \quad (5)$$

We show in the Appendix A that the phase component of the SxPSD approximatively expresses as $arg\left[P_{x_1x_2}(t,f)\right] \approx 2\pi f\theta(t)$. In this way, the time-varying delay $\theta(t)$ can therefore be estimated by fitting at each instant t a linear curve of the SxPSD phase along the frequency axis. For practical reasons, the coherence function between $x_1(t)$ and $x_2(t)$ is preferred instead of SxPSD. Indeed, the coherence function normalizes the SxPSD so that the estimation is independent of the signals power:

$$coh_{x_1x_2}(t,f) = \frac{P_{x_1x_2}(t,f)}{\sqrt{P_{x_1x_1}(t,f)}\sqrt{P_{x_2x_2}(t,f)}} \quad (6)$$

This expression can be evaluated by considering the estimations $P_{x_1x_2}(t,f)$, $P_{x_1x_1}(t,f)$ and $P_{x_2x_2}(t,f)$. This leads to the method called *interspectrum and autospectrum averaging* described in the following. Alternatively, assuming that the magnitudes are deterministic, the coherence is reduced to the averaging of the phase exponential. This leads to the second estimation method, so called in the following *coherency averaging*.

Interspectrum and autospectrum averaging. The first method for the evaluation of Eq. (6) is based on the mathematical expectation estimations of each term in the following expression:

$$cohF_{x_1x_2}(t,f) = \frac{\mathbf{E}_t\{S_{x_1x_2}(t,f)\}}{\sqrt{\mathbf{E}_t\{S_{x_1x_1}(t,f)\}}\sqrt{\mathbf{E}_t\{S_{x_2x_2}(t,f)\}}} \quad (7)$$

The $\mathbf{E}_t$ symbol stands for the mathematical expectation over time that is realized with the Welch averaging method. The SxPSD and SPSDs are estimated by averaging the windowed interspectrum $S_{x_1x_2}(t,f)$ and windowed autospectra $S_{x_1x_1}(t,f)$ and $S_{x_2x_2}(t,f)$.

In the digital domain, this leads to:

$$cohF_{x_1x_2}(n,k) = \frac{\sum_{i=-I/2}^{I/2} S^{(W)}_{x_1x_2}(n-iL,k)}{\sqrt{\sum_{i=-I/2}^{I/2} S^{(W)}_{x_1x_1}(n-iL,k)}\sqrt{\sum_{i=-I/2}^{I/2} S^{(W)}_{x_2x_2}(n-iL,k)}} \quad (8)$$

where $S^{(W)}_{x_1x_2}(n,k)$ is the digital instantaneous interspectrum between x_1 and x_2 evaluated around time n on W-width window. Similarly, $S^{(W)}_{x_1x_1}(n,k)$ and $S^{(W)}_{x_2x_2}(n,k)$ stand for the digital instantaneous spectra of x_1 and x_2, respectively. The value L is the shift parameter between each slice of the Welch periodogram.

Coherency averaging. The second method consists in applying the expectation operator on instantaneous phase exponentials as follows:

$$coh\kappa_{x_1x_2}(t,f) = \mathbf{E}_t\left\{e^{j\phi_{x_1x_2}(t,f)}\right\} \quad (9)$$

where the notation $\phi_{x_1x_2}(t,f)$ corresponds to the angle of the windowed complex interspectrum function $S_{x_1x_2}(t,f)$. The $\mathbf{E}_t$ symbol is realized in the digital domain by a local averaging on $2d+1$ points around each instant n using the formula:

$$coh\kappa_{x_1x_2}(t,f) = \sum_{i=-d}^{i=d} \frac{S_{x_1x_2}(n-i,k)}{|S_{x_1x_2}(n-i,k)|} \quad (10)$$

A similar approach has been previously proposed for the phase synchrony detection from EEG signals [16].

For each coherence estimation method ($cohF_{x_1x_2}(t,f)$ and $coh\kappa_{x_1x_2}(t,f)$), the phase component is derived. The time-varying