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Towards real-time estimation of muscle-fiber conduction velocity using delay-locked loop

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Abstract—Decrease in muscle-fiber conduction velocity (MFCV) during sustained contraction has been widely accepted as myoelectric manifestation of muscle fatigue. Several methods have been proposed in the literature for MFCV estimation by analysing surface electromyography (EMG), e.g., cross-correlation (CC) function and maximum likelihood (ML). However, for all the available methods, windowing of the EMG signal and computationally demanding calculations are required, limiting the possibility to continuously monitor muscle fatigue in real time. In the present study, an adaptive scheme is proposed that permits real-time estimation of MFCV. The proposed scheme is based on a delay-locked loop (DLL). A second-order loop is adopted to track the delay variation over time. An error filter is employed to approximate a ML estimation in case of colored noise. Furthermore, the DLL system is extended for multichannel CV estimation. The performance of the proposed method is evaluated by both dedicated simulations and real EMG signals. Our results show the accuracy of the proposed method to be comparable to that of the ML method for much lower (1/40) computational complexity, especially suited for real-time MFCV measurements. Use of this method can enable new studies on myoelectric fatigue, possibly leading to new insight on the underlying physiological processes.

Index Terms—Electromyography, Maximum-likelihood estimation, Muscle fatigue, Muscle-fiber conduction velocity, Phase-locked loop.

I. INTRODUCTION

Surface Electromyography (EMG) has been analyzed and processed in a variety of applications including ergonomics, prosthesis control, movement gait analysis, sports, and rehabilitation programs. The amplitude of the surface EMG, estimated by the root mean square value of the recorded signal, is frequently studied as an indicator of neuromuscular activity and force production [1], [2]. The mean frequency of the surface EMG, calculated as the first statistical moment of the EMG amplitude spectrum, is widely employed as an indicator of myoelectric fatigue during sustained contraction [3], [4].

Furthermore, the conduction velocity (CV) of the action potentials propagating along the muscle fibers is a basic physiological parameter that is related to type and diameter of muscle fibers, muscle temperature, ion concentration, and motor unit firing rate [5]. In particular, the muscle-fiber conduction velocity (MFCV), together with the EMG mean frequency, is widely used as an indicator of neuromuscular fatigue [3], [6]. An increase in muscle fatigue is associated with a decrease in the MFCV [3], [6].

The MFCV can be estimated by analysing the surface EMG signals recorded using two or more electrodes placed along the muscle fibers with known inter-electrode distance [7], [8]. The time delay between the recorded EMG signals reflects the time it takes for the action potentials to propagate along the muscle

fiber. Thus, the MFCV is obtained after dividing the inter-electrode distance by the estimated time delay between the recorded EMG signals. Typical values reported in the literature for the MFCV are in the order of few m/s [9], [10].

Several methods have been proposed in the literature for the MFCV estimation, including calculation of the phase difference [7], [11], detection of spectral dips [8], maximization of the cross-correlation (CC) function [12], and maximum likelihood (ML) [13]–[15]. For the use of the spectral dips method, one of the main issues is the large variance in the dip detection, owing to the variance of the estimated power spectrum that is used to calculate the dips [16]. The cross-correlation function is discrete in the time lag, limiting the resolution of the estimated CV due to the time-sampling rate [16]. To improve the resolution of the CC method, an interpolation over the estimated values is required. The phase difference and ML method are both implemented in the frequency domain, permitting CV estimation without resolution limitation. However, the phase difference method is more sensitive to additive noise than the other methods [17]. The ML method is suggested to be reliable and robust for CV estimation, as it takes all the available channels into consideration [13], [14], [18].

For all these available methods, segmentation of the recorded signal using a sliding time window, e.g., 0.5–2 s [3], is required, producing only one CV estimate in each segment. Continuous CV estimation during the entire contraction period can only be achieved by overlapping (moving each window by one sample). However, considering the computing time required for each estimation, none of the available methods can be used for real-time CV assessment. In some clinical settings, e.g., for advanced rehabilitation programs, real-time CV assessment is useful to provide real-time information on myoelectric fatigue, which can be used for adaptive optimization of the training parameters.

In the present study, a novel adaptive scheme with low computing complexity is proposed for CV estimation, enabling real-time monitoring of myoelectric fatigue. The proposed method is designed based on a phase locked loop (PLL) system, which has been extensively investigated in the literature and employed in a variety of communication and biomedical applications [19]–[23]. The operation of a PLL system can be divided into two phases: the acquisition phase and the tracking phase. The acquisition is the initial phase of the estimation, in which the parameter misadjustment is forced to zero and, therefore, the estimated parameter approaches to the real value. When the acquisition has succeeded, the misadjustment between the estimated parameter and the actual parameter is small enough for the PLL system to enter the

tracking phase.

The PLL system is modified for delay estimation and then referred to as delay-locked loop (DLL) in the present study. The DLL system is based on least-squares (LS) estimation, which produces ML estimation if the noise is additive, white, and Gaussian [23], [24]. An error filter is employed in the present study in order to approximate a ML estimation for colored noise.

Multichannel EMG signals have been widely used by previous authors for CV estimation in order to increase robustness [13], [15]. The DLL system is therefore extended for multichannel delay estimation. The performance of the proposed method is evaluated by dedicated simulations as well as by real EMG signals recorded on the biceps brachii by a high-density electrode grid during fatiguing isometric contraction.

II. METHOD

A. Two-channel delay estimation using DLL

We first consider estimating the delay between two EMG signals $x(k)$ and $r(k)$ recorded by two electrodes placed along the muscle fibers ($k = 1, 2, \dots, K$ is the discrete time variable). Figure 1 shows the signal model and the scheme of the proposed DLL system for delay estimation. $r(k)$ is assumed to be a delayed version of $x(k)$ and corrupted by Gaussian noise $w(k)$, i.e.,

$$r(k) = x(k - \theta) + w(k). \quad (1)$$

The delay between the two signals, θ , is prior unknown. $\hat{\theta}$ is an estimation of θ . Subtraction of an artificially delayed version of $x(k)$, $x(k - \hat{\theta})$, from $r(k)$ yields an error

$$e(\hat{\theta}, k) = r(k) - x(k - \hat{\theta}) = x(k - \theta) - x(k - \hat{\theta}) + w(k). \quad (2)$$

If the estimate $\hat{\theta}$ coincides with the actual delay θ , $e(\hat{\theta}, k)$ contains purely the noise $w(k)$. Otherwise, $e(\hat{\theta}, k)$ will also contain a residual signal component $x(k - \theta) - x(k - \hat{\theta})$, which is likely to increase the energy of $e(\hat{\theta}, k)$ relative to the situation where it contains purely noise. Therefore, the

Fig. 1. The signal model and the proposed second-order DLL system.

minimization of the error energy $\varepsilon(\hat{\theta}) = \sum_{k=1}^K e^2(\hat{\theta}, k)$ can be used as a criterion for setting $\hat{\theta}$. This is referred to as LS parameter estimation [25].

With our prior knowledge about the CV of the action potentials propagating the muscle fibers, it is possible to restrict $\hat{\theta}$ to a small range in which $\varepsilon(\hat{\theta})$ is convex, with just a single minimum. In this case, the minimization of $\varepsilon(\hat{\theta})$ can be determined by locating the zero-crossing of its gradient $\xi(\hat{\theta})$, given by

$$\xi(\hat{\theta}) = \frac{\partial}{\partial \hat{\theta}} \sum_{k=1}^K e^2(\hat{\theta}, k) = 2 \sum_{k=1}^K e(\hat{\theta}, k) \frac{\partial}{\partial \hat{\theta}} e(\hat{\theta}, k). \quad (3)$$

Inserting (2) into (3) and omitting the components that do not depend on $\hat{\theta}$, the gradient $\xi(\hat{\theta})$ can be expressed as

$$\xi(\hat{\theta}) = -2 \sum_{k=1}^K e(\hat{\theta}, k) s(\hat{\theta}, k), \quad (4)$$

where $s(\hat{\theta}, k)$ is the derivative of $x(k - \hat{\theta})$ with respect to $\hat{\theta}$ and is referred to as the signature of the parameter misadjustment. Since $s(\hat{\theta}, k) = dx(k - \hat{\theta})/d\hat{\theta} = -dx(k - \hat{\theta})/d(k - \hat{\theta})$, the signature $s(\hat{\theta}, k)$ can be obtained from $x(k - \hat{\theta})$ by a differentiator, as indicated in Fig. 1 by d/dk .

A LS estimation of θ corresponds to a search for the value of $\hat{\theta}$ that forces the gradient $\xi(\hat{\theta})$ to be zero, which can be implemented by adaptive closed-loop schemes in real-time applications, as shown in Fig. 1. In this scheme, a instantaneous measure of the gradient, i.e., $\eta(k)$, is used, as given by

$$\eta(k) = e(\hat{\theta}, k) s(\hat{\theta}, k). \quad (5)$$

Since $\hat{\theta}$ is restricted in a small vicinity of θ , $x(k - \hat{\theta})$ can be approximated by means of a first-order Taylor series, as given by

$$x(k - \hat{\theta}) \simeq x(k - \theta) - \Delta \cdot s(\theta, k), \quad (6)$$

where $\Delta = \theta - \hat{\theta}$ is the parameter misadjustment. Inserting (6) into (2) yields

$$\begin{aligned} e(\hat{\theta}, k) &\simeq x(k - \theta) - [x(k - \theta) - \Delta \cdot s(\theta, k)] + w(k) \\ &= \Delta \cdot s(\theta, k) + w(k). \end{aligned} \quad (7)$$

Inserting (7) into (5), the instantaneous gradient can be expressed as

$$\eta(k) \simeq [\Delta \cdot s(\theta, k) + w(k)] s(\hat{\theta}, k). \quad (8)$$

As $\hat{\theta}$ is assumed to be close to θ , $s(\hat{\theta}, k)$ will be approximately equal to $s(\theta, k)$. Then, we obtain

$$\eta(k) = e(\hat{\theta}, k) s(\hat{\theta}, k) \simeq \Delta \cdot s^2(\theta, k) + w(k) s(\theta, k). \quad (9)$$

Therefore, $\eta(k)$ is proportional to the parameter misadjustment Δ , while the term $w(k) s(\theta, k)$ introduces an additive disturbance to the estimation of Δ . Such disturbance causes fluctuations in the estimated parameter $\hat{\theta}$ around its steady-state value, referred to as gradient noise.

The LS estimation produces a ML estimation if the noise $w(k)$ is additive, Gaussian, and white [24]. A ML estimation is desirable in many applications as it has profitable bias and variance properties [23], [26]. However, the noise $w(k)$ may

be colored rather than white, for which the LS estimation does not correspond to a ML estimation. An error filter is therefore employed to whiten the frequency components of the noise $w(k)$ in order to approximate a ML estimation [23]. Studies have suggested a high-pass filter to be suitable [23].

The DLL system acts to drive the average value of $\eta(k)$ in (9) to zero. If $e(\hat{\theta}, k)$ is filtered by the error filter, also the signature $s(\hat{\theta}, k)$ should be filtered by the same filter, as shown in Fig. 1. As a result, filtered versions of $e(\hat{\theta}, k)$ and $s(\hat{\theta}, k)$, indicated as $\tilde{e}(\hat{\theta}, k)$ and $\tilde{s}(\hat{\theta}, k)$, respectively, are used for the calculation of $\eta(k)$ as

$$\eta(k) = \tilde{e}(\hat{\theta}, k) \tilde{s}(\hat{\theta}, k). \quad (10)$$

In order to obtain $\hat{\theta}$, a second order delay loop is employed to force $\eta(k)$ to be zero [23], as shown in Fig. 1. This loop is divided into two processes for the separate estimation of the constant delay and the delay deviation $\hat{\theta}_d$. The parameter $\hat{\theta}$ is updated by

$$\begin{aligned} \hat{\theta}_d(k+1) &= \hat{\theta}_d(k) + k_{d\theta} \cdot \eta(k), \\ \hat{\theta}(k+1) &= \hat{\theta}(k) + k_\theta \cdot \eta(k) + \hat{\theta}_d(k+1), \end{aligned} \quad (11)$$

where k_θ is the adaptation factor for the constant delay while $k_{d\theta}$ is the adaptation factor for the delay deviation. For a sufficiently high sampling frequency, the discrete second-order DLL in Fig. 1 can be characterized by a damping factor ζ [dimensionless] and a natural frequency [rad/s] [23], which are related to k_θ and $k_{d\theta}$ as

$$\zeta = \frac{k_\theta}{2\sqrt{k_{d\theta}}} \quad (12)$$

$$\omega_n = \sqrt{k_{d\theta}}. \quad (13)$$

The damping factor ζ is typically in the order of 0.5 to 2 [22].

The DLL scheme shown in Fig. 1 includes two phases: the acquisition phase and the tracking phase. In the acquisition phase, the parameter misadjustment Δ can still be large and the instantaneous estimate $\eta(k)$ does not necessarily provide optimum control information. In the tracking phase, the misadjustment is small in order to allow the estimator to work reliably [27].

It is important to notice that, in the DLL scheme shown in Fig. 1, $x(k)$ is only available for discrete time variable while the estimated parameter $\hat{\theta}$ in (11) is likely not to be an integer value. Therefore, a linear interpolation is employed in practice for the calculation of $x(k - \hat{\theta})$, given as

$$x(k - \hat{\theta}) = x(j) + [x(j+1) - x(j)] \cdot (k - \hat{\theta} - j), \quad (14)$$

where j is the integer part of $k - \hat{\theta}$, with $k - \hat{\theta} > 0$.

B. Extension to multichannel delay estimation

Multichannel EMG signals are widely used for CV estimation in order to increase robustness [13], [15]. The proposed DLL scheme is therefore extended for multichannel applications. We consider multichannel EMG signals recorded by a $N_r \times N_c$ electrode grid with its columns parallel to the muscle fibers, as shown in Fig. 4. It may be assumed that signals detected in one column from adjacent rows are delayed by a

fixed parameter θ and embedded in additive, Gaussian noise $w_{rc}(k)$. Therefore, for each column, the signal recorded at the first row can be modeled as

$$\begin{aligned} x_{1c}(k) &= x_{rc}(k - (r-1)\theta) + w_{rc}(k), \\ k &= 1, \dots, K; r = 2, \dots, N_r; c = 1, \dots, N_c \end{aligned} \quad (15)$$

where r is the indicator of rows, N_r the number of rows, c the indicator of columns, N_c the number of columns, and K is the number of samples.

Taking $x_{1c}(k)$ as reference signal for each column, the two-channel DLL in Fig. 1 can, therefore, be extended for multichannel delay estimation, as shown in Fig. 2. Details of η detection and θ update in Fig. 2 are described in Fig. 1. For the multichannel DLL system, the error between $x_{1c}(k)$ and the artificially delayed version of $x_{rc}(k)$ is denoted as $e_{rc}(\hat{\theta}, k)$ and calculated as

$$e_{rc}(\hat{\theta}, k) = x_{rc}(k - (r-1)\theta) - x_{rc}(k - (r-1)\hat{\theta}) + w_{rc}(k). \quad (16)$$

Accordingly, the compound error energy $\varepsilon(\hat{\theta})$ is given by

$$\varepsilon(\hat{\theta}) = \sum_{c=1}^{N_c} \sum_{r=2}^{N_r} \sum_{k=1}^K e_{rc}^2(\hat{\theta}, k). \quad (17)$$

The gradient expressed in (4) and the instantaneous measure of the gradient expressed in (10) are then replaced by (18) and (19) respectively, as

$$\xi(\hat{\theta}) = -2 \sum_{c=1}^{N_c} \sum_{r=2}^{N_r} \sum_{k=1}^K e_{rc}(\hat{\theta}, k) s_{rc}(\hat{\theta}, k), \quad (18)$$

$$\eta(k) = \sum_{c=1}^{N_c} \sum_{r=2}^{N_r} \tilde{e}_{rc}(\hat{\theta}, k) \tilde{s}_{rc}(\hat{\theta}, k) = \sum_{c=1}^{N_c} \sum_{r=2}^{N_r} \eta_{rc}(k), \quad (19)$$

where $s_{rc}(\hat{\theta}, k)$ is the derivative of $x_{rc}(k - (r-1)\theta)$, $\eta_{rc}(k)$ the instantaneous gradient for each signal x_{rc} , and $\tilde{e}_{rc}(\hat{\theta}, k)$ and $\tilde{s}_{rc}(\hat{\theta}, k)$ are the error-filtered versions of $e_{rc}(\hat{\theta}, k)$ and $s_{rc}(\hat{\theta}, k)$. After obtaining $\eta(k)$, $\hat{\theta}$ is updated by (11), the same as the two-channel DLL.

C. Experimental measurements

Ten subjects (8 males and 2 females, age = 28 ± 5 years) volunteered for the EMG measurements. The EMG measurements were performed with a dedicated setup realized in our previous study [28], whose scheme is shown in Fig. 3. Briefly, a motor generated a fully-controlled force that was applied to the subject through a pulley interface. The enrolled subjects were instructed to sit on the bench of the setup and hold a handle with their back straight and their elbow at 90° . This position was monitored through a visual feedback implemented by a rotary encoder embedded in the setup. The isometric maximum voluntary contraction (MVC) of the right arm was first measured by a load-cell embedded in the aluminum bar, according to a protocol described in our previous study [29], [30]. After establishing the MVC, the subjects maintained the same position and performed a 13-s isometric contraction on the right arm. The adopted load for each subject was 80% of his/her MVC.

Fig. 2. Scheme of the multichannel DLL system.

During the 13-s isometric contraction, surface EMG was recorded on the biceps brachii using a high-density electrode grid, which consists of 8×8 contact Ag/AgCl electrodes with diameter of 2 mm and inter-electrode distance of 4 mm. The electrode grid was placed between the tendon at the elbow side and the muscle belly, with its columns aligned with the muscle fibers, as shown in Fig. 4. To avoid crossing the fiber innervation zone, the operator performed careful visual inspection on the detected EMG signals, which were acquired by a 64-channel Refa[®] amplifier (TMS International, Enschede, the Netherlands). The sampling frequency was 1024 Hz and the resolution of the ADC was 22 bits. No filtering was implemented during the recording. Active shielding and grounding of the cables were used for reduction of the electromagnetic interference. The ground electrode was placed on top of the clavicle on the right side of the subject.

D. Validation

1) *In silico*: The performance of the proposed adaptive DLL scheme for MFCV estimation was evaluated by means

of dedicated simulations based on real signals. A 12-s signal was extracted from the 13-s EMG recordings, starting from the 0.5 second. This signal was then artificially delayed to simulate the measurements of the same signal by the other electrodes on the grid within the same column (8 channels). An arbitrary fractional delay of 1.25 samples was considered. With the given inter-electrode distance of 4 mm and the sampling frequency of 1024 Hz, this delay corresponds to a CV of approximately 3.3 m/s. Colored noise was then added to each channel. The added noise was generated by filtering white Gaussian noise using a fourth-order Butterworth bandpass filter with cutoff frequencies 10 and 400 Hz, as suggested in previous studies [31]. The signal-to-noise ratio (SNR) was 15 dB, which is in the range of the SNR values adopted in EMG simulation studies (2-22 dB) [32].

The multichannel DLL system was evaluated by the simulation signals with and without error filtering in order to test the effect of the error filter. When involved, the error filter was implemented by a second-order IIR high-pass filter [23] with a cutoff frequency of 250 Hz, as most of the EMG

Fig. 3. Scheme of the measurement setup.

spectral components are located below 250 Hz. The model parameters ζ and ω_n were selected by dedicated pre-test. ζ was set to be 1.2 to obtain stable response. In order to test the influence of ω_n on the performance of the second order loop, two natural frequencies were implemented, which were $\omega_n = 0.005$ and $\omega_n = 0.002$, corresponding to the adaptation parameters $k_\theta = 1.2 \times 10^{-2}$, $k_{d\theta} = 2.5 \times 10^{-5}$ and $k_\theta = 4.8 \times 10^{-3}$, $k_{d\theta} = 4 \times 10^{-6}$, respectively.

The initial value of $\hat{\theta}_d$ was set to be 0 while the initial value of $\hat{\theta}$ can be derived based on our prior knowledge of MFCV, CV_{Prior} , as given by

$$\hat{\theta}_{Initial} = d \cdot f_s / CV_{Prior}, \quad (20)$$

where $d = 0.004$ m is the inter-electrode distance of the adopted electrode grid and $f_s = 1024$ Hz is the sampling frequency. By assuming a CV_{Prior} of 4.5 m/s, which is around the average CV value reported in the literature [9], [10], a value of 0.9 sample was obtained for the initial $\hat{\theta}$.

2) *In vivo*: The proposed method was also evaluated with real EMG signals recorded during 80% MVC isometric contraction, as described in Section II-C. The time interval between 0.5 to 12.5 s of the contraction was adopted for the analysis in order to avoid including transients at the beginning and end of the contraction. All the EMG signals were first normalized to obtain zero mean and unit variance. In order to remove the common mode potential, the normalized signals were bipolarized along the muscle fiber by subtracting the adjacent electrodes signals in the same column, leading to 8 parallel columns of 7 bipolar signals. Figure 5 shows an example of bipolar signals recorded by one column of the electrode grid.

The derived bipolar signals were then band-pass filtered between 20 and 450 Hz using a fourth-order Butterworth filter. The delay between adjacent bipolar signals in each column, $\hat{\theta}$, was adaptively estimated using the proposed multichannel DLL scheme (Fig. 2). The DLL scheme was implemented both with and without the error filter, the same as the simulation signal. The CV of the action potentials propagating along the muscle fibers was then calculated as $CV = d \cdot f_s / \hat{\theta}$.

In the implementation, ζ and ω_n were set to be 1.2 and 0.002, respectively. The initial $\hat{\theta}_d$ was 0 while the initial $\hat{\theta}$ was set to be 0.5 sample by assuming a CV_{Prior} of 8 m/s, which

Fig. 4. High-density electrode grid indicating the muscle fiber orientation.

is almost the maximum value of CV reported in the literature [9], [10]. Choosing this value allows to test the performance of the DLL system under extreme conditions.

For evaluation, the CV estimated by the proposed DLL system was compared with that estimated by the ML method, since the ML method has been suggested as an accurate and reliable method for CV estimation [13], [14], [18]. To this end, the selected 12-s bipolar EMG signal (0.5-12.5 s) was first divided into a series of 1-s, overlapped epochs [33], [34]. Each epoch was moved by one sample in order to produce a continuous CV estimation, the same as the DLL system. The CV in each epoch was then calculated using the ML method [34] and then compared with the CV estimated by the DLL system at the same time instant.

To evaluate the computing complexity, the execution time of the proposed method was also determined and then compared to that of the ML method. In addition, since the CC method has lower computing complexity than the ML method, the computing time of our method was also compared to that of the CC method. The same sliding window used in the ML method was also employed in the CC method. All the analysis was implemented in Matlab[®] 2014b (MathWorks, Natick, MA). The adopted computer was a HP Compaq Elite CMT PC, with an Inter(R) Core(TM) i5-2500 CPU @ 3.30 GHz processor.

Fig. 5. Example of the EMG signals recorded by one column of the electrode grid.

Fig. 6. Delay estimation for the simulation signals ($\zeta = 1.2$): a) No error filtering, $\omega_n = 0.005$; b) Error filtering, $\omega_n = 0.005$; c) No error filtering, $\omega_n = 0.002$.

III. RESULTS

A. In-silico results

Figure 6 shows the estimated delay for the simulation signals using the proposed DLL scheme with and without error filtering. For all cases, $\hat{\theta}$ converges to the correct value $\theta = 1.25$ after the acquisition phase. Convergence speed depends on the adaptation factor k_θ ($k_\theta = \omega_n^2$), i.e., a larger k_θ leads to a fast convergence. The stability of the second-order loop depends on the damping factor ζ . The adopted ζ value, 1.2, ensures stable response of the loop without oscillation.

The presence of Gaussian noise in the simulation signals does not affect the speed of convergence but does introduce gradient noise, i.e., steady-state fluctuation in $\hat{\theta}$ around the desired value $\theta = 1.25$, as shown in Fig. 6 a. The gradient noise may be reduced by error filtering (Fig. 6 a and b). Furthermore, the gradient noise is also influenced by the adaptation factor k_θ . While leading to a fast convergence, a larger k_θ also causes larger gradient noise (Fig. 6 a and c).

B. In-vivo results

Figure 7 shows an example illustrating the estimated delay for the real EMG signals using the proposed adaptive DLL scheme with and without error filtering. For both cases, $\hat{\theta}$ converges very fast and then the DLL locks up and enters the tracking phase. For all the 10 measurements, the acquisition phase takes less than 0.3 s. Furthermore, the gradient noise is remarkably reduced when the error filter is implemented. After convergence, the estimated delay increase along time, indicating a decrease in the MFCV, which is considered as a myoelectric manifestation of muscle fatigue [3].

In order to compare the DLL system with the ML method, only the time interval between 1 to 12 s of the DLL results is taken into account, denoted as steady-state, as the ML method produces the first results at the end of the 1st second. After error filtering, the CV estimates in the steady-state for all the 10 subjects are in the range between 2.6-4.3 m/s, which is in

Fig. 7. Example of the estimated delay for real EMG signals ($\zeta = 1.2$, $\omega_n = 0.002$): a) No error filtering; b) Error filtering.

line with the value of the MFCV reported in literature [9], [10]. Furthermore, the CV estimates using the adaptive DLL scheme show good agreement with the CV estimated in separated epochs by the ML method, as shown in Fig. 8. The average CV estimated during the steady-state over all the 10 subjects is 3.29 ± 0.25 m/s and 3.25 ± 0.32 m/s for the proposed method and the ML method, respectively. The difference between the average CV estimated during the steady-state period over all the 10 subjects by the two different methods is not significant, indicated by a paired Student's t -test ($p > 0.05$).

The average execution time on an entire data set (12 s), estimated by ten repeated tests over all the subjects is 16 ± 0 s, 183 ± 3 s, and 646 ± 6 s for the proposed methods, the CC method, and the ML method, respectively.

Fig. 8. Example of the estimated CV by the proposed method and the ML method.

IV. DISCUSSION

This study proposes a novel adaptive scheme for MFCV estimation, which comprises a special case of a PLL system referred to as a DLL system. The DLL system permits real-time time-delay estimation in the recorded EMG signals, enabling to continuously monitor the velocity of the EMG signals as a myoelectric manifestation of muscle fatigue during sustained contractions. The DLL system is initially designed for two-channel CV estimation and then extended to multichannel application, enabling the use of available EMG signals acquired by a high-density electrode grid and, therefore, leading to an increased robustness for the CV estimation [14], [15].

A second-order DLL system is implemented in the present study in order to estimate the delay deviation (frequency deviation in the PLL system), as suggested in [23]. However, the second-order system may introduce instability in the loop response. The damping factor ζ , determining the stability of the second-order system, is therefore optimized by dedicated pre-test in order to obtain stable response. Furthermore, our simulation results indicate that the nature frequency of the second order system, ω_n , to determine the convergence speed of the loop and to possibly influence the steady-state gradient noise. Therefore, the nature frequency is also optimized as a tradeoff between convergency speed and steady-state accuracy.

In order to filter the error signal and approximate a ML estimation, an error filter is employed in the proposed DLL system. Studies have also suggested that an error filter implemented in a PLL system can significantly reduce the gradient noise [23]. Our results confirm that, as expected, the gradient noise is remarkably reduced by error filtering (Fig. 6 and 7). However, it should also be noticed that the convergence speed of the DLL system decreased slightly when the error filter is implemented.

The gradient-based optimization employed in the DLL system (Section II-A) is based on restricting the trial parameter $\hat{\theta}$ in a small vicinity of the real parameter θ . For a large difference between θ and the initial $\hat{\theta}$, the acquisition phase can be difficult. However, previous studies have suggested the MFCV to be in the range of few m/s, e.g., 4 m/s [9], [10]; it is therefore possible to restrict $\hat{\theta}$ in a sufficiently small vicinity of θ . Studies have shown that PLL systems lock up almost instantaneously if the difference between θ and $\hat{\theta}$ is sufficiently small [22]. In the present study, a CV of 8 m/s is adopted to derive the initial $\hat{\theta}$ (0.5 sample) for the real EMG signals, which is close to the maximum value of CV reported in the literature [9], [10]. In such worst case, the DLL system locks up within less than 0.3 s (Fig. 7) for all the subjects. It is therefore reasonable to expect an even faster acquisition phase when a lower CV, e.g., 4 m/s, is used to derive the initial $\hat{\theta}$. Such fast convergence rate indicates the feasibility of the proposed method for real-time continuous CV monitoring in myoelectric fatigue studies.

After implementing the error filter, the CV estimates obtained by our method are in agreement with the CV obtained by the ML method [13]–[15], as shown in Fig. 8, confirming the accuracy of the proposed approach. In addition, the ML method is typically performed on separated epochs and

produces an average CV in each epoch, while the DLL-based method allows continuous monitoring of the MFCV in real time, in which lies the main novelty of the proposed method. Although the ML method can provide continuous CV estimation by overlapping (moving one sample each window), it can not be implemented online due to its computing time (646 s), which is over a factor 40 larger than the DLL method (16 s). Furthermore, the computing time of our method is even lower than that of the CC approach (183 s), which has lower computing complexity and accuracy as compared to the ML method.

V. CONCLUSION

A DLL-based adaptive system is proposed in the present study for MFCV estimation. An error filter is included in the DLL to approximate a ML estimation in case of colored noise. A second-order loop is employed to track the delay variation. Furthermore, the DLL system is extended for multichannel delay estimation. Our results show good performance for the proposed method, comparable with the ML method suggested by previous authors. In addition, due to its significantly lower complexity, our method is more suited for real-time continuous estimation of the MFCV, possibly bringing new insight on fatigue studies using MFCV as an indicator.

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