Comparison Between Parametric and Non-Parametric Approaches for Time-Varying Delay Estimation with Application to Electromyography Signals

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Abstract. Muscle fiber conduction velocity (MFCV) is generally measured by the estimation of the time delay between electromyography recording channels. In this paper, we compare performances of two well-known approaches: parametric and non-parametric. The results indicate that the non-parametric approach can obtain better performance when the noise is strong (SNR = 10 dB). With the low noise level, the parametric approaches become more interesting.

Keywords: Muscle Fiber Conduction Velocity · EMG · Multi-channel acquisition · Fatigue · Time-varying delay estimation

1 Introduction

Due to the easy interpretability, Muscle Fibers Conduction Velocity (MFCV) becomes an useful physiological indicator of electromyography (EMG) activity. Specially, the MFCV is considered as an interesting indicator in many EMG fields, *e.g.* monitoring neuromuscular degenerative diseases [1] and the assessment of pain in the case of fibromyalgia [2]. Moreover, it is also applied in many fundamental studies on motor control whose applications include both the medical field and ergonomics.

As mentioned in [3], the MFCV can be estimated from intramuscular or surface electromyography recordings. However, the estimation of the MFCV from the surface EMG (sEMG) signals is complex because this task requires the advanced tools for processing signals. Ideally, it is required that the shape of the detected sEMG signals must not be changed over the entire length of the fiber. However, this condition is difficult to fulfill in practice due to the following reasons: first, the electrical activity cannot be characterized as a pure propagation because of the different conduction velocity of motors. In addition, as mentioned in [4], the tissues separating the muscle fibers and the recording electrodes are in-homogeneous along the direction of propagation, and hence they affect the shape of the sEMG signals during the propagation. Finally, the quality

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of the signals also is affected from the noises caused from movements, contact between electrodes and skin.

From the reasons above, we provide several difficulties when estimating the MFCV as follow: first, the estimation procedure is based on data modeling. However, it is worthy noting that a method that too strongly depends on the model cannot adjust to reality. Second, the sEMG signals suffers from several limitations due to anatomical problems and changes in the action potential volume conductor that impact the conduction velocity estimation. There are three factors which affect the sEMG signal: the non-stationary property of the data [5], the change in conductivity properties of the tissues separating electrodes and muscle fibers, and the relative shift of the electrodes with respect to the origin of the action potential [4].

In order to extend the estimators to the multichannel case which would face to various local signal-to-noise ratios (SNRs), the SNR parameters should be taken into account in the time-delay estimator design. Hence, the multichannel scheme should be developed, follows the steps as follow: at first, we have to investigate the two-channel scheme with a constant time delay. In the next step, the best estimators which can be obtained from the previous study will be extended to the time-varying delay case. Finally, in the last step, we will specifically design methods for multi-channel recordings based on the study at the second step. Most recently, the authors in [6] proposed a method in which only the first step is presented. In [7], a parametric approach, *i.e* Maximum - Likelihood estimation (MLE) of time varying delay for two channels of sEMG signals, were investigated. In this approach, the delay with unknown model is cut into many slices and is tested via Monte-Carlo simulations. As presented in [7], the proposed method obtains the better performance as compared with the time-frequency one in [5,8]. In [9], we used the best estimators of the generalized cross correlation that indicated in [6] by sliding the window through over the data in order to take into account the non-stationary of the data. In this paper, we will compare the performance of the best estimator of the parametric and non-parametric approaches to classify them and to determinate if their performance are sufficient for practical applications. Moreover, the Root Mean Square Error (RMSE) theoretical will be shown in order to compare with the performance experimental presented in [6]. Although this work is still limited in the case of two channels, we will extend the best estimators to the multi-channels case from the obtained results of this paper.

The paper is organized as follow: In Sect. 2, the models of signals and time varying delay will be defined. In Sect. 3, the generalized cross correlation and the Maximum likelihood estimation will be presented. Section 4 presents the simulation results with first synthetic sEMG data. In Sect. 5, we conclude the paper.

2 Model of Time-Varying Delay (TVD) and sEMG Synthetics Signals

2.1 Signal Model

Considering the sEMG signal $s(n)$ propagation between channel 1 and channel 2, a simple analytical model of two observed signals $x_1(n)$ and $x_2(n)$ in a discrete time domain, without shape differences, is the following:

$$\begin{aligned} x_1(n) &= s(n) + w_1(n), \\ x_2(n) &= s(n - \theta(n)) + w_2(n), \end{aligned} \tag{1}$$

where $\theta(n)$ is the propagation delay between the two signals, and $w_1(n)$ and $w_2(n)$ are assumed to be independent, white, zero mean, additive Gaussian noises, of equal variance σ^2. Once $\theta(\mathrm{n})$ is estimated, the MFCV can simply be deduced by $\mathrm{MFCV}(\mathrm{n}) = \Delta\mathrm{e}/\theta(\mathrm{n})$ where e stands for the inter-electrode distance, which is taken as 5 mm in the following. The digitization step is processed at the sampling frequency $\mathrm{F_s} = 2048\,\mathrm{Hz}$. We detail below the two models used for the time varying delay (TVD) function as well as the way for generating synthetic sEMG signals with predefined TVD functions.

2.2 Inverse Sinusoidal Model

In this study, we used the inverse sinusoidal model of TVD defined as follows:

$$\theta(\mathrm{n}) = \mathrm{F_s}\frac{5.10^{-3}}{5 + 3\sin(0.2\mathrm{n}2\pi/\mathrm{F_s})} \tag{2}$$

This model has been previously proposed in [5]. It takes into account reasonable physiological variations of MFCV that may be encountered during dynamical exercise situations. In particular, the minimum and maximum MFCV values are $2\,m.s^{-1}$ and $8\,m.s^{-1}$ respectively. The maximum acceleration value is $2.5\,m.s^{-2}$. One period of the sine wave is considered corresponding to 5 s observation duration or to equivalently 10000 data samples.

2.3 Delayed Signal Generation

The signals are synthetic ones and are generated according to the following analytic Power Spectral Density (PSD) shape proposed by Shwedyk *et al.* in [10] and written in the following equation as

$$\mathrm{PSD}(\mathrm{f}) = \frac{\mathrm{k}\mathrm{f_h^4}\mathrm{f^2}}{(\mathrm{f^2} + \mathrm{f_l^2}).(\mathrm{f^2} + \mathrm{f_l^2})^2}. \tag{3}$$

An example of sEMG PSD shape is given in [11], where the low and high frequency parameters are fixed as $\mathrm{f_l} = 60\,\mathrm{Hz}$ and $\mathrm{f_h} = 120\,\mathrm{Hz}$ respectively. The parameter k is a normalization factor. The first channel is generated by linear filtering a white Gaussian noise with the impulse response corresponding to this PSD (*i.e.* the inverse Fourier transform of the square root of the previous PSD shape. Once the first channel is generated, its delayed version is created thanks to the sinc-interpolator [12]:

$$\mathrm{s}\left(\mathrm{n}-\theta\left(\mathrm{n}\right)\right)=\sum_{\mathrm{i}=-\mathrm{p}}^{\mathrm{p}}\mathrm{sinc}\left(\mathrm{i}-\theta\left(\mathrm{n}\right)\right)\mathrm{s}\left(\mathrm{n}-\mathrm{i}\right) \tag{4}$$

The parameter p is the filter length and is fixed to p=40. Finally, both channels are distorted by adding White Gaussian noise at a given signal to noise ratio (SNR) level.

3 Methods

3.1 Fourier Phase Coherency Method (CohF)

This method was proposed in [5]. The local Fourier coherence of two signals $x_1(t), x_2(t)$ is

$$\mathrm{CohF}\left(\mathrm{t},\mathrm{f}\right)=\frac{\mathrm{E_t}\left\{\mathrm{P_{x_1x_2}}\left(\mathrm{t},\mathrm{f}\right)\right\}}{\sqrt{\mathrm{E_t}\left\{\mathrm{P_{x_1x_1}}\left(\mathrm{t},\mathrm{f}\right)\mathrm{P_{x_2x_2}}\left(\mathrm{t},\mathrm{f}\right)\right\}}}, \tag{5}$$

where $\mathrm{P_{x_1x_2}}\left(\mathrm{t},\mathrm{f}\right)=\mathrm{X_1}\left(\mathrm{t},\mathrm{f}\right)\mathrm{X^*}_2\left(\mathrm{t},\mathrm{f}\right)=\left|\mathrm{P_{x_1x_2}}\left(\mathrm{t},\mathrm{f}\right)\right|\mathrm{e}^{\mathrm{i}\emptyset_{\mathrm{x_1x_2}}\left(\mathrm{t},\mathrm{f}\right)}$ is the local cross spectrum, $\mathrm{X_1}\left(\mathrm{t},\mathrm{f}\right)$ and $\mathrm{X_2}\left(\mathrm{t},\mathrm{f}\right)$ are the local Fourier transform of the signals $\mathrm{x_1}\left(\mathrm{t}\right)$, $\mathrm{x_2}\left(\mathrm{t}\right)$: and given as follow:

$$\mathrm{X_i}\left(\mathrm{t},\mathrm{f}\right)=\int_{-\infty}^{\infty}\mathrm{h}\left(\tau-\mathrm{t}\right)\mathrm{x_i}()\mathrm{e}^{-\mathrm{i}2\pi\mathrm{f}\tau}\mathrm{d}\tau, \tag{6}$$

The function $h(t)$ is the Hanning weighting window function that restricts the Fourier transform around the time instant t. The asterisk refers to the conjugate of the signal. The expectations E_t are estimated by the Welch method. Each N-samples window is divided in three N/2 samples Hanning weighted windows with 50 % of overlapping. It can be shown that

$$\mathrm{P_{x_1x_2}}\left(\mathrm{t},\mathrm{f}\right)\approx\mathrm{P_{ss}}\left(\mathrm{t},\mathrm{f}\right)\mathrm{e}^{-2\mathrm{i}\pi\mathrm{f}\theta\left(\mathrm{t}\right)} \tag{7}$$

Since all the other terms in the coherence function are positive and real, the phase term in CohF(t,f) entirely contains at each time instant the delay (t).

3.2 The Generalized Cross-Correlation (GCC) Method

In [6], the GCC method proposed in [13] has been evaluated and tested with two synthetics sEMG signal in the case of time delay constant. The fractional part of the time delay(TD) was calculated by the parabolic interpolation [14]. In [9], we used the best estimator of GCC method which identified in [6] and slide the window over the data in order to take into account the non-stationarity of the data and the change over time of the delay.

3.3 Maximum Likelihood Estimation (MLE)

This method was derived in [7], the MLE method for a TVD which follow a polynomial model was detailed and applied to the TVD with unknown model (Inverse sinusoidal model) by cutting de TVD and sliding over the data. In this paper, we used this method as a reference to compare with the proposed methods and the "CohF" method in [5].

4 Results and Discussions

When the signals are continuous and duration T, the theoretical values for the mean square error (MSE) of the time delay estimators obtained by generalized cross-correlation were evaluated in [15] as

$$\mathrm{MSE} = \mathrm{E}\left\{\left(\hat{\theta}-\theta\right)^{2}\right\} = \frac{\int_{-\infty}^{\infty} \mathrm{A(f)}_{\mathrm{x_1 x_2}}(\mathrm{f})^{2}\mathrm{df}}{\mathrm{T}.\left[\int_{-\infty}^{\infty} \mathrm{B(f)}_{\mathrm{x_1 x_2}}(\mathrm{f})\,\mathrm{df}\right]^{2}} \tag{8}$$

where $w\,(\mathrm{f})$ is the weight function called the processor which were defined in [6] for each processor by

$$\mathrm{A\,(f)} = (2\pi \mathrm{f})^{2}\left[\mathrm{G_{w_1 w_1}\,(f)\,.G_{ss}\,(f) + G_{w_2 w_2}\,(f)\,.G_{ss}\,(f) + G_{w_1 w_1}\,(f)\,.G_{w_2 w_2}\,(f)}\right] \tag{9}$$

$$B(f) = (2\pi f)^{2} G_{ss}(f). \tag{10}$$

Figure 1 shows the square root of these MSE values. These values theoretically in seconds were reduced to values in samples, for the sampling frequency of $F_s = 2048\,\mathrm{Hz}$ previously considered. This allows us to understand the magnitude of these theoretical errors with regard to the experimentally calculated errors. We see that these theoretical curves deteriorate over shorter observation time as in the experimental case [6].

A Monte-Carlo simulation with 100 independent runs was performed for each signal to noise ratio (SNR) value in order to study the noise impact of these estimators. In this work, two synthetic sEMG signals have the same value of SNR = 10, 20, 30, 40 dB respectively. Duration of the signals is 5 s.

Figure 2 shows the evaluation results for an overlapping of 50 % of the slices for the parametric method. The statistical mean of the root mean square error (RMSE) between the expected time-varying delay and the estimated one is reported as a function of the signal-to-noise ratio (SNR). The graph shows no significant performance improvement with respect to the non overlapping case.

It is now interesting to compare the performance of two proposed improvements, namely the parametric approach (coefficients estimations of a low-order polynomial function over several successive short time slices) and non-parametric approach (sliding local estimations by GCC methods).

Figure 3 shows a comparison between the two tracks of proposed improvement compared with the reference method CohF. For a SNR = 10 dB, the error obtained with the parametric method is two times greater than the non-parametric approaches (local GCC). However, the parametric method becomes

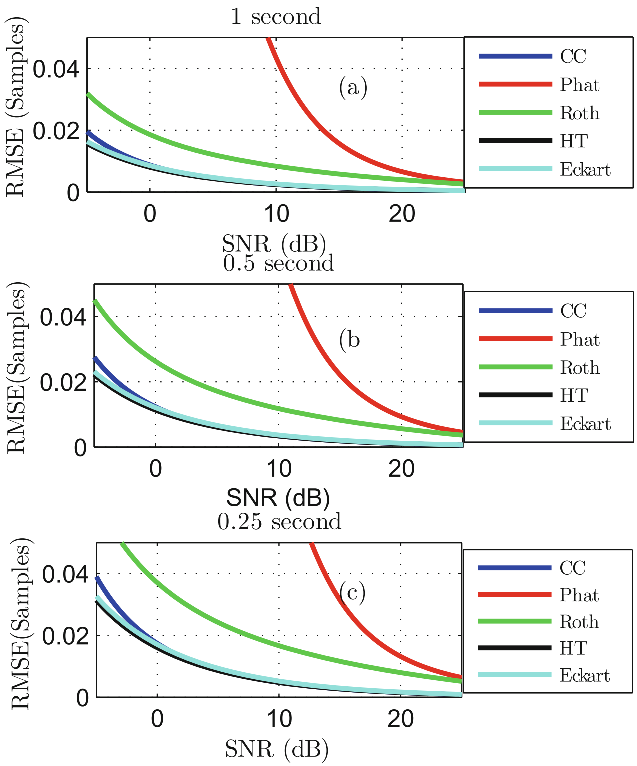

Fig. 1. Square root of the theoretical MSE based SNR for the 5 tested methods and three experimental periods 1 s (a) - 0.5 s (b) - 0.25 s (c). The reference method is the CC method. For comparative purposes, the errors calculated for continuous data were converted from second to sample, with $F_s = 2048\,Hz$

interesting in favorable noise condition (SNR = 40 dB). Note that the sliding CC method is relatively insensitive to the noise level. In the case of real data, this method is attractive because improvements displayed by the Eckart processor require knowledge of the shape of the PSD of the signal and the noise.

Figure 4 represents the mean value of the RMSE as a function of SNR for the methods Eckart and CC. The length of signals was set equal to 500 ms in the stationary case (1024 points), which corresponds to the length of the sliding time slide used for the non-stationary case. This allows to highlight the deterioration of errors of the delay estimation in the case non-stationary case compared with the stationary case. The processor Eckhart in this study provides a significant improvement compared to the CC method. The impact time-varying delay compared to the case of time delay constant, resulting in an error of about 0.01 samples, regardless of the SNR.

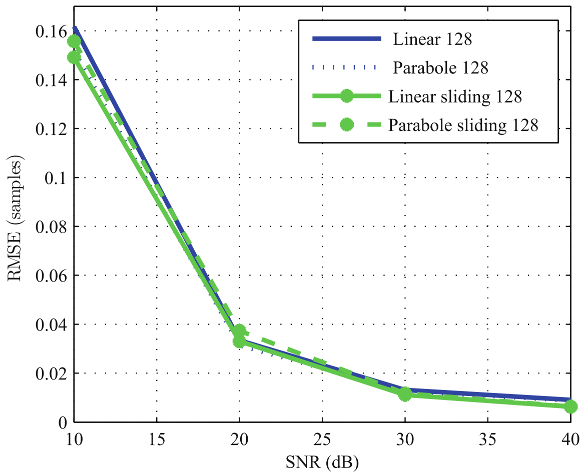

Fig. 2. Mean of RMSE as a function of SNR for parametric methods. Newton method with 128 points linear (solid line) or parabolic (dotted line) estimations; disjoint successive slices (blue) or successive overlapping slices of 50 % (green) (Color figure online)

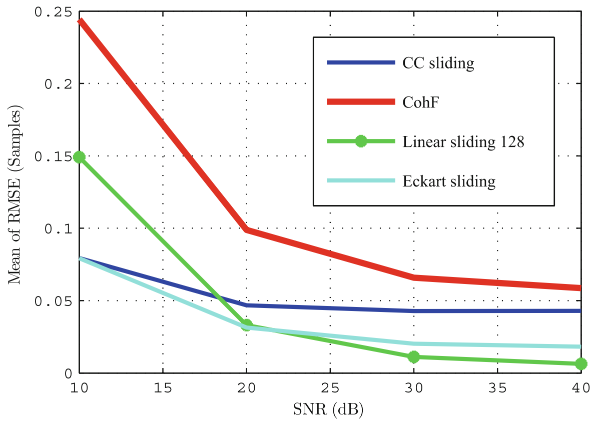

Fig. 3. Comparison of two proposed improvements (parametric and non-parametric methods). Mean of RMSE as a function of SNR. Non parametric methods: one point sliding processors Eckart (cyan) and CC (dotted blue) applied on 1024 points. windows; phase coherence method [5] (red); Parametric method: Newton method with 128 points linear slices estimation and 50 % overlapping (green). (Color figure online)

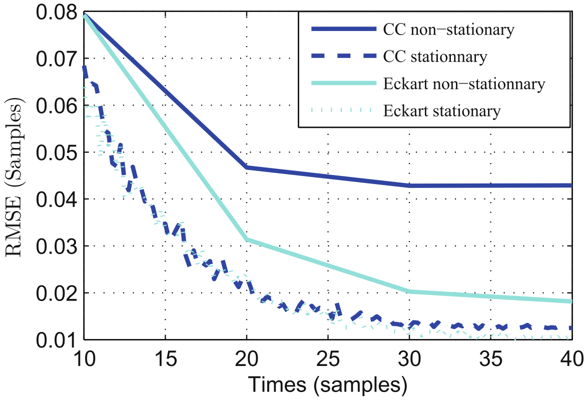

Fig. 4. Mean of RMSE as a function of SNR in the stationary case for a period of 500 ms, which is 1024 points (dashed curves) and in the non-stationary case, for a period of 5 s, or 10240 samples (features continuous). GCC method with the processor Eckart (cyan) and cross-correlation method-CC (blue). (Color figure online)

5 Conclusions

In this paper, we proposed to compare the best results of the parametric and non-parametric approach for the estimation of time-varying delay applied to MFCV evaluation of sEMG signals. The results indicate that the non-parametric approach is the best in the case where the noise is strong (SNR = 10 dB) but in the case where noise is weak, the parametric approach becomes the most interesting one. Our future works are the application of these methods to the real data. Also, the estimation in the multi-channel case will be investigated.

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