# **How much can we trust the electromechanical delay estimated by using electromyography?**

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*Abstract-In* **this paper different estimation techniques are evaluated for the assessment of Electromechanical Delay (EMD). The following techniques are compared for benchmarking purposes: envelope estimation and thresholding, with different subjective combinations of filters and thresholds, and a double threshold statistical detector (DTD). Performance are compared in terms of bias, standard deviation and erroneous detections of the**  estimations. DTD showed higher **repeatability of results, guaranteed by the objective settings based on the statistical characteristics of the algorithm.** 

# I. INTRODUCTION

Electromechanical delay (EMD) has been defined as the time delay between the onset of muscular electrical activity and the onset of the motor task, the so called motor output. It has been proved that an accurate assessment of EMD can improve the knowledge of central nervous system commands driving the movements, of muscular synergies and of apparent anomalies between myoelectric activity and body segment motion [l].

Basically, EMD is affected by mechanical factors (i.e. stiffness) that change the rate of shortening of series elastic components. Moreover it has been demonstrated that the stiffness is altered by events such as initial muscle length [2] and muscle loading [3]. EMD appeared to be dependent on muscle fibers composition, on number, type and excitation frequency of the motor units recruited in a contraction, and on fatigue phenomena related to alterations in membrane excitability. Since many years, EMD has been stated to be between 30 and 100 ms [4] with a mean value relatively constant with respect to movement complexity and movement duration [5], although it can be lengthened after fatigue [6]. Pathology can alter EMD as it has been observed: a reduction in cerebral palsy [7], an increase after ligament reconstruction [8]. During complex protocols, especially in dynamic conditions, results on EMD reported in the literature can be contradictory. For example, when studying EMD in fatiguing protocols some studies revealed an increase, while other authors reported no significant changes in EMD [1]. The controversial findings have affected the effectiveness of the EMD results, and have driven some researchers to doubt on the same existence of the EMD phenomenon and to consider it as a simple mathematical artifact. The main explanation of these contradictory findings is related to the processing of signals to extract information on EMD, which implies the detection of the onset of both myoelectric activity and mechanical output. The onset of muscular activity is determined mainly by estimating and thresholding the envelope of sEMG signals, a technique that is used also to study the relationship between the myoelectric activity and the mechanical force exerted during the movement. This kind of studies [9], looking at the chance to estimate muscular force from sEMG recordings, correctly skipped the problem of EMD and focused on the similarity between sEMG envelope and moments profiles on the joints. Some operators mis-interpreted the results, after filtering sEMG signals without considering phase delay and then the EMD cancellation, and stated the inexistence of EMD. One method of determining EMD makes use of a pre-processing of sEMG thus giving rise to the sEMG envelope, generally obtained with a full-wave rectifier followed by an integrator (a moving average or a lowpass filter), thus obtaining the so called integrated EMG (IEMG). This technique has been widely studied and its characteristics have been analyzed in order to obtain optimal performance in the case of stationary signals (isometric contractions).

In spite of its wide use, this processor presents some drawbacks which affect the quantitative validation of the estimation results: the main one can be found in the arbitrary choice of the used low-pass filter. In particular, its time constants range from 10 ms  $[10]$  to 150 ms  $[11]$ according to the subjective choices made by the experimenters. Different time constants for the low-pass filter do not guarantee repeatability of results and comparison among different laboratories. Large time constants prevent the detection of short activations but guarantee "smoother" envelopes, whereas short time constants follow rapid variations in the envelope but imply a high estimation variance. This affects inter and intra individual repeatability of the envelopes [12] preventing a correct information exchange.

Moreover, when the envelope is used for the detection of muscle activation intervals, such as in the EMD assessment, the filtering can change the phase of the signal affecting temporal detection.

The detection of muscular activity implies the subjective setting of a threshold on IEMG to discriminate background noise from the signal of the active muscles. The subjective settings for filter cut/off frequency (producing different time delays) and threshold chosen without correctly considering the signal to noise ratio (SNR) of the recordings, imply that results of muscular timing are not reproducible [13].

Therefore, this work deals with the evaluation of suitable procedures for EMD assessment, that do not imply subjective settings and thus aims at a large applicability. The authors will answer the question in the title by using quantitative results and thus providing insights on proper processing procedures to validate findings on EMD.

# 11. MATERIALS AND METHODS

The estimation of EMD implies detecting the muscular activity onset. To this end, the following approaches will be compared on both simulated and experimental signals: 1) envelope estimation and thresholding, after filtering with FIR filters with symmetric coefficients but different cut-off frequencies and threshold values; 2) adaptive filtering and thresholding with an automatic algorithm already developed by some of the authors [14]; 3) a statistical double threshold detector [15].

These techniques will be tested on simulated signals for benchmarking and then will be applied to real signals recorded during isokinetic tasks of the lower limbs.

# *A. Envelope estimation and thresholding (EET)*

In EET the cut-off frequency of the low-pass filter is difficult to be decided in advance. The following cut-off frequencies for low-pass FIR filters with 300 coefficients, have been used:  $\{3, 10, 20\}$  Hz (that is time constants respectively of about  $\{60, 20, 10\}$  ms). These values are chosen to deal with dynamic sEMG.

# *B. Adaptive envelope estimation and thresholding (AEE)*

In order to take into account the non-stationarity of the signals in dynamic conditions, also the adaptive envelope estimation (AEE) technique has been tested. This approach is very useful when dealing with dynamic exercise where the characteristics of the signals change through time and then the choice of a single cut-off frequency for the whole signal can be misleading. As stated in [16], the best filter length for each signal sample can be adaptively chosen, by minimizing, step by step, an error function involving not only the amplitude of the signal, but its derivative as well. In [14] the adaptive iterative technique has been shown to be independent on the initial choice of the filter length and its convergence has been demonstrated. In the current work, the envelope has been differently thresholded. In particular the following approaches have been tested: 1) muscular onset as the first point to rise above the 99% confidence interval of baseline for 20 ms (confidence interval of the baseline estimated on 50 samples belonging to a no-activity zone) as in [17]; 2) thresholds set as respectively the (10, 20, 30}% of the maximum value of the signal envelope.

# *C. Double Threshold Detector (DTD)*

The DTD [15] presents good performance and it is not affected by operator's subjective settings because the thresholds are automatically calculated according to the SNR of the signals by means of an iterative procedure that updates the SNR estimate. The convergence is obtained when the estimated SNR reaches a plateau. The effects of spurious transitions are controlled because the algorithm rejects transitions shorter than 30 ms, which have no meaning from a biomechanical point of view. In simulation tests the statistical detector allows a percentage of 5% of misdetection; the estimate typically presents a bias lower than 10 ms and a standard deviation lower than 15 ms, for SNR values higher than 8 dB.

#### *D. Simulations*

sEMG signals  $s_k$  have been simulated by referring to the Hogan and Mann [18] model  $s_k = w_k n_k + e_k$  where the modulating waveform  $w_k$  contains the information on muscular activity,  $n_k$  and  $e_k$  are realizations of ergodic gaussian processes whose power values have been designed in order to have well determined SNR values.

The SNR values used are chosen in the set {8, 10, 15, 20}dB, a typical range of noise values detectable in sEMG signals. For each SNR value, the procedure for generating the simulated data has been the following: 1) generation of 30 white Gaussian sequences  $\{n_k\}$ ; 2) amplitude modulation with a rectangular waveform  $w_k$ ; 3) frequency characterization by a band-pass shaping filter [19]; 4) generation of 30 white Gaussian sequences  $\{e_k\}$ , to obtained the desired SNR values. The muscular activity gives rise to a movement delayed by 100 ms, as it generally happens in real experimental exercises.

# *E. Experimental Proofs*

A MERAC isokinetic device was used to analyze a maximal knee flexo-extension exercise, within the range of flexion  $0^{\circ}-90^{\circ}$ . Subjects sat in an ergonomic adjustable seat with the thigh and the back supported, and were fastened to the seat by a seatbelt placed above the pelvis and a belt fixing the proximal part of the thigh. By controlling the body posture in that way, the knee is supposed to be the only moving joint. The protocol of the exercise consists of a cycle of knee flexo-extensions carried on at different velocity values [120, 180, 240,  $300$ <sup>o</sup>/s.



Fig. 1. Signals recorded during a maximal knee flexo-extension exercise at  $120^{\circ}/s$ From top to bottom the angular displacement, VL, VM and BF are shown.

The sEMG signals from three muscles of the dominant leg, Vastus Lateralis (VL), Vastus Medialis (VM), Biceps Femoris (BF), were recorded by the MT8-3 telemetric system at 1000 **Hz.** The signal representing the angular position of the knee was acquired by a potentiometer. An example is in Fig. 1. From top to bottom the angular displacement and muscles are shown.

TABLE I Bias and standard deviation in the EMD detection on simulated data.

		8 dB		10dB		15 dB		$20$ dB	
		$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	σ
<b>EET</b>									
3Hz	$3\sigma$	111.3	50.1	101.7	51.8	107.6	54.6	122.7	41.8
	10%	227.9	7.2	226.6	9.5	217.7	20.5	176.7	48.0
	20%	217.9	20.0	211.8	26.5	149.9	63.4	65.7	9.7
	30%	193.0	41.0	161.7	60.1	63.7	46.9	33.0	10.7
10 Hz	$3\sigma$	45.9	61.3	33.0	46.0	23.8	45.6	24.7	46.5
	10%	229.7	2.9	229.1	3.7	224.3	8.8	67.1	82.6
	20%	225.3	8.3	218.3	15.2	27.6	58.4	3.1	2.4
	30%	194.2	55.7	75.1	97.8	4.7	3.0	7.9	4.1
20Hz	$3\sigma$	33.5	40.6	29.4	41.3	24.1	42.6	22.1	43.6
	10%	230.0	2.1	229.5	2.6	223.0	7.8	17.9	39.2
	20%	225.1	6.8	204.2	35.2	13.6	32.9	11.1	2.8
	30%	117.4	84.8	17.6	38.1	14.3	3.0	16.0	3.2
<b>AEE</b>	$3\sigma$	35.5	58.2	36.7	57.9	43.7	54.8	45.7	53.7
	10%	231.0	$\Omega$	231.0	$\theta$	231.0	$\mathbf{0}$	31.3	40.2
	20%	231.0	$\mathbf{0}$	229.9	3.8	12.7	8.3	14.5	10.4
	30%	204.5	50.9	27.2	53.8	7.4	7.6	9.5	8.6
<b>DTD</b>		3.1	4.6	1.9	2.7	1.0	2.1	0.8	2.1

## 111. RESULTS

Results obtained on simulated series are reported in Table I, in terms of bias and standard deviation in the electromechanical delay estimation. The values are expressed in milliseconds. By bold characters, bias values lower than 10 ms have been outlined. If a threshold of *30*  of the baseline confidence interval is used, then high cutoff frequencies (20 Hz) are needed to obtain acceptable better performance, the same applies to thresholding at

30% of the maximum sEMG value. The cut-off frequency does not affect the detection when using respectively 10% and 20% of the maximum as thresholds for SNR values lower than 15 dB.

DTD approach shows bias lower than 3.5 ms and standard deviation lower than *5* ms for each tested SNR value. The RMSE error is always lower than 6 ms.



Fig. 2. Erroneous transitions obtained with the different processing approaches for each isokinetic exercise.

**TABLE II** Mean value and standard deviation of EMD estimation by DTD, EET (3Hz,10%), EET (3Hz,20%) for VL, VM and BF in experimental isokinetic exercise. Velocity values are [120, 180, 240, 300]<sup>o</sup>/s.

120°/s	VL		VM		BF		
	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$	
DTD	76.0	9.9	64.0	4.2	92.7	6.5	
EET (3Hz; 10%)	186.3	33.9	156.6	28.7	145.3	8.3	
EET (3Hz; 20%)	129.0	21.1	100.6	19.0	106.7	11.2	
$180^{\circ}/s$	VL		VM		BF		
	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$	
<b>DTD</b>	71.7	4.0	71.7	5.7	70.0	1.7	
EET (3Hz; 10%)	176.7	12.1	138.0	8.2	124.3	22.1	
EET (3Hz; 20%)	126.0	7.8	85.3	6.1	81.0	26.0	
$240°$ /s	VL		VM		BF		
	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$	
<b>DTD</b>	87.0	10.9	69.0	22.1	66.2	40.3	
EET (3Hz; 10%)	193.5	9.3	164.5	18.9	129.2	28.8	
EET (3Hz; 20%)	143.7	12.5	112.5	26.2	83.0	27.4	
$300^\circ/s$	VL		VM		BF		
	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$	
<b>DTD</b>	88.5	19.6	103.5	28.4	60.6	7.8	
EET (3Hz; 10%)	206.7	14.7	192.2	29.5	174.8	24.3	

Results on experimental signals have been evaluated in terms of mean value and standard deviation of the EMD calculated along the exercise cycles, and of the percentage of erroneous transitions. This percentage is defined as the number of cycles where there are false positive or false negative detections, divided by the total movement cycles and multiplied by 100.

The erroneous transitions have been evaluated for each isokinetic exercise (that is velocity values [120, 180, 240, *30O]"ls)* with the compared processing techniques. The only techniques preventing erroneous transitions are the DTD, and the EET when using 3Hz cut-off frequency and thresholds at 10% and 20% of the maximum peak value of the sEMG envelope.

The EMD values obtained by EET are greater than those obtained by DTD and also greater than the typical values presented in the literature. The standard deviation values, which can be interpreted as a robustness criterion of the estimation along all the exercise cycles, depend on the velocity of execution, but are more stable in DTD. DTD shows EMD values according to those presented in the literature and lower values of standard deviation at  $120^{\circ}/s$  and  $180^{\circ}/s$ .

# IV. DISCUSSION OF RESULTS

The obtained results show the subjectivity in the use of EET approaches. **A** first drawback can be found in the baseline definition, necessary to estimate the threshold: in fact, if in simulations it is possible to know exactly where the signal is, the same is not possible in experimental cases. Thus the baseline definition needs either an operator intervention or an automatic detection procedure which should be based on SNR estimation. This drawback affects all the threshold procedures. The erroneous transitions obtained by EET affect the robustness of the estimate and decrease the feasibility of these approaches. Tests on synthetic time series, by neglecting erroneous transitions, demonstrate that EET are greatly affected by the SNR of the signals, and give some acceptable estimate only for SNR grater than 10 dB with medium-high cut-off frequencies and with high thresholds. Decreasing the SNR, high thresholds do not allow good estimations. Results obtained with real signals demonstrate that EET, when setting 3Hz cut-off frequencies, can be used without erroneous transitions. However, on synthetic signals 3Hz filtering has revealed high biased results.

In conclusion, DTD guarantees the best performance on both synthetic and real signals in terms of consistency, sensitivity and specificity of the estimate. Moreover, DTD is the only fully automatic technique which can be applied without using any subjective setting.

# V. CONCLUSIONS

In this work some procedures for EMD assessment have been tested. Particular attention has been devoted to the automatic approaches, based on the statistical characteristics of the signal, that do not imply subjective settings by the experimenter. The procedures have been applied on both simulated and experimental signals recorded during knee flexo-extensions isokinetic exercises. The question presented in the title can be answered by stating that DTD approach guarantees the best results in terms of bias, standard deviation, erroneous transitions of the estimation. This approach is then proposed by the authors as the best choice for muscular activation and then EMD assessment.

#### **REFERENCES**

[4] PR Cavanagh, PV Komi, "Elcctromcchanical dclay in human skclctal muscle under concentric and eccentric contractions", *Euv J Appl Physiol Occwp Physiol.,* vol. 42(3), pp. 159-63, 1979.

[5] GJV. Schenau, PJM Boots, G Degroot, RJ Snackers, WWLM Vanwocnscl, "The constraincd control of forcc and position in multijoint movements", *Neuroscience,* vol. 46, pp. 197-207, 1992.

[6] AP Marsh, PE Martin, "The relationship between cadence and lower extremity EMG in cyclists and noncyclists", *Med. Sei. Sports Exerc.,*  vol. 27, pp. 217-225, 1995.

[7] PV Granata, AJ Ikeda, MF Abel, "Electromechanical delay and reflex response in spastic cerebral palsy", *Arch Phys Med Rehahil,* vol. 81, pp. 888-894,2000.

[8]M Jorgc, ML Hull, "Analysis of EMG mcasurcmcnts during bicyclc pedalling", *J. Biomech.,* vol. 19, pp. 83-694, 1986.

[9] SJ Olney, DA Winter, "Predictions of knee and ankle moments of force in walking from EMG and kinematic data", *J. Biomech.,* vol. 18(l), pp. 9-20, 1985.

[lo] AE Patla, "Some characteristics of EMG patterns during locomotion: implications for the locomotor control process", *J. Motor Behavior,* vol. 17, pp. 443-461, 1985.

[11] V Medved, S Tonkovic, "Locomotion diagnostics: some neuromuscular and robotics aspects", *IEEE Eng. in Med. and Biol. Mag.,*  vol. *6,* pp. 23-28, 1991.

[12] DA Winter, HJ Yack, "EMG profiles during normal human walking: stride-to-stride and intcr-subject variability", *Electroencephalogv. Clin. Neurophysiol.,* vol. 67, pp. 401-41 1, 1987.

[13]] RA Bogey, LA Barnes, J Perry, "Computer algorithms to characterize individual subject EMG profiles during gait", *Arch. Phys. Med. Rehabil.,* vol. 73, pp. 835-841, 1992.

[14] T D'Alessio, S. Conforto, "Extraction of the envelope from surface EMG signals: an adaptive procedure for dynamic protocols", *IEEE Engineering in Med. and Biol. Magazine,* vol. *6,* pp. 55-61,2001,

[15] P Bonato, T D'Alcssio, M Knaflitz, **"A** statistical mcthod for thc measurement of muscle activation intervals from surface myoelectric signal during gait", *IEEE Trans. on BME,* Vol. 45(3), pp.287-299,1998.

[16] T D'Alessio, "Some results on the optimization of digital surface proccssor for surfacc EMG signals", *Electroencephalogr. Clin. Neurophysiol.*, pp. 625-643, 1984.

[17] RP Di Fabio, "Reliability of computerized surface electromyography for determining the onset of muscle activity", *Phys Ther.,*  vol. 67, pp. 43-48, 1987.

[18] N Hogan, RW Mann, "Myoelectric signal processing: Optimal estimation applied to electromyography. Part I: derivation of the optimal myoprocessor", *IEEE Trans. on BME,* vol. 27, pp. 382-395, 1980.

[19] FB Stulcn, CJ Dc Luca, "Frcqucncy Parameters of thc Myoclcctric Signal as a Mcasurc of Muscle Conduction Vclocity", *IEEE Trans. on BME,* vol. 28, pp. 512-523, 1981.

<sup>[1]</sup> S. Zhou, "Acute effect of repeated maximal isometric contraction on clcctromcchanical dclay of kncc cxtcnsor musclc", *J. Electromyogr. Kinesiol.,* vol. 6(2), pp. 117-127, 1996.

<sup>[2]</sup> MD. Grabiner, RN Robertson, KR Campbell, "Effects of fatigue on activation profiles and relative torque contribution of elbow flexor syncrgists", *Med Sci Sports Exerc.,* vol. 20(1), pp. 79-84, 1988.

<sup>[3]</sup> RW Simmons, C. Richardson, "Effects of different types of mechanical load on the duration of the initial agonist pulse", *Exp. Brain Res.,* vol. 92 **(3),** pp. 524-527, 1993.