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Unsupervised Stochastic Strategies for Robust Detection of Muscle Activation Onsets in Surface Electromyogram

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Abstract

Surface electromyographic (sEMG) data impart valuable information concerning muscle function and neuromuscular diseases especially under human movement conditions. However, they are subject to trial-wise and subject-wise variations, which would pose challenges for investigators engaged in precisely estimating the onset of muscle activation. To this end, we posited two unsupervised statistical approaches—*screeplot elbow detection* (SPE) heavily relying on the threshold choice and the more robust *profile likelihood maximization* (PLM) that obviates parameter tuning—for accurately detecting *muscle activation onsets* (MAOs). The performance of these algorithms was evaluated using the sEMG dataset provided in [1] and the simulated sEMG created as explained therein. These sEMG signals are reported to have been collected from the *biceps brachii* and *vastus lateralis* of 18 participants while performing a biceps curl or knee extension, respectively. The acquired sEMG signals were first preconditioned with the *Teager-Kaiser energy operator*, and then either supplied to the SPE or to the PLM or to a state-of-the-art algorithm. The mean and median errors between the MAO time in milliseconds estimated by each of the algorithms and the *gold standard* onset time derived in [1] were computed. The outcome of a PLM variant, namely, PLM-Laplacian, has been found to have good agreement with the gold standard, i.e., an absolute median error of 9 ms and 21 ms in the simulated and the actual sEMG data, respectively; whereas, the errors produced by the other algorithms are statistically significantly larger than that incurred by the PLM-Laplacian according to *Wilcoxon ranksum test*. In addition, the advocated approach does not necessitate parameter settings, lending itself to be

flexible and adaptable to any application, which is a unique advantage over several other methods. Research is underway to further validate this technique by imposing various experimental conditions.

Keywords

Change detection; muscle activation onset; profile likelihood; surface electromyography

I. INTRODUCTION

Change detection, being a classical signal processing problem, allured researchers from diverse backgrounds due to its potential application in fault detection, diagnosis, prediction of natural calamities, and monitoring in biomedicine [2]. An active research area that falls under this category is the detection of *muscle activation onsets* (MAOs) in the surface electromyographic (sEMG) signal, since it has crucial implications in the field of medicine [3]—diagnosis of neuromuscular, neurological, and psychomotor disorders—in addition to rehabilitation and sport science [4]–[6]—control of neuro-prosthesis, human-machine interaction, grasp recognition, and biofeedback system. Importantly, sEMG analyses of clinical relevance warrant accurate identification of onset, offset, and duration of the EMG burst, as exemplified below. The temporal analysis of muscle recruitment can unravel an enhanced muscle coactivation due to aging during locomotion [7] as well as unique muscle activation patterns pertaining to stroke [8], Parkinson's disease [9], and cerebral palsy [10]. Furthermore, this analysis led to the quantification of electromechanical delay under various conditions, which is an essential input variable in musculoskeletal modeling [11].

Nevertheless, this problem persists to be challenging due to the following reasons. The presence of background noise during the sEMG recording affects the signal-to-noise ratio (SNR), thereby contributing to the degradation of MAO detection accuracy in subjects with and without neuromuscular disorders [12], [13]. Moreover, the power-line noise could potentially interfere with the sEMG signal while being measured [14]. Another source of difficulty arises from slowly increasing muscle activity, known as *long ramps* [12]. Additionally, the measured sEMG signal also accounts for the signal patterns generated by motor units of the neighboring muscles, namely, *myoelectric cross-talk* [15]; owing to their resemblance to a real muscle activation pattern with a low amplitude, these artifacts may falsely be construed by most algorithms as desirable signal [14].

In view of the impediments listed above, the MAO detection by visual inspection is recommended for small datasets; however, it is admittedly laborious, time-consuming, and subjective—contingent on one's expertise leading to nonreproducible results. Therefore, algorithm-based approaches are on the rise, which may broadly be classified into the following categories: threshold detector [16], [17]; wavelet template matching [12], [18]; statistical criterion determination [1], [6], [13], [19]–[23]; *Teager-Kaiser energy operator* (TKEO) conditioning [24]–[26]; and sample entropy analysis [27].

The threshold-based algorithms are grounded on the premise that the amplitude of the (filtered) sEMG signal concomitant with an onset occurrence should exceed a threshold

value, which in turn is deduced from the mean power of the background noise [28]. Albeit less cumbersome to implement, the downside is that the choice of the threshold is application specific and cannot adapt well to continuous changes in background noise. As an advancement, the double-threshold algorithm was intended to alleviate the false alarm probability and the detection bias at the expense of computational resources [16].

In contrast to threshold-based methods, those inspired by statistical principles, e.g., *maximum likelihood* (ML) algorithms, prove to be reasonably accurate even for low levels of EMG activity with only a moderate increase in the computational complexity [21]. Interestingly, unlike threshold-based signal-power estimation procedures that are too sensitive to signal parameters such as the SNR or background activity level, the statistically optimized algorithms are reputed to be more robust [29]. Besides, this class of methods would in general not require additional information concerning the signal properties [14]. One must however bear in mind that the *a priori* knowledge of the probability density functions (PDFs) of the muscle activations and the baseline activities would further enhance the effectiveness of such methods, e.g., CUSUM algorithm introduced in [30]. On the contrary, most of the ML-based algorithms simply assume that the underlying distributions are *Gaussians*. For instance, Ying and Wall built a probabilistic transition model (PTM) for the sEMG signal under the assumption that the signal and noise follow a normal distribution [23]. By estimating the probability of each signal point being in the noise region, given its neighborhood amplitudes and the transition models, the muscle onset is predicted. Most recently, in [1] and [31], Tenan *et al.* reported an experimental evaluation of three established methods—*linear envelope*, TKEO-preprocessed linear envelope, and *sample entropy*—and three statistical methods, namely, *general time series mean/variance*, *sequential and batch processing of parametric and nonparametric tools*, and *Bayesian changepoint detection* (BCD) proposed in [32]. Among the six methods, the BCD supplied with the rectified EMG was found to perform the best in terms of reliability and accuracy, where the hyperparameter of the prior (p_0) and the signal-to-noise level (w_0) were set to be 0 and 0.2, respectively, and the posterior probability was assigned a value within the interval [0.60 0.95].

In the present work, we modeled the muscle activations and the baseline activities with a more realistic *Laplace* PDF, since the corresponding data seem to follow a super-Gaussian distribution. It has also been demonstrated how the detection accuracy would deteriorate when the Laplace PDF is replaced by a Gaussian PDF in Section III-B. Unlike the family of ML-based approaches akin to ours that is hinged on the *generalized likelihood ratio* as in [33], we maximize a *profile likelihood function* expressed in (8) because of its benefits that are deferred to Section II-D. Furthermore, the onset detection accuracy attained by our scheme in a rigorous empirical study surpasses that resulted from the variants of a threshold-based scheme and a few notable state-of-the-art methods, and the improvement remains statistically significant. Since the TKEO has been acclaimed to aggrandize the contrast between the muscle activations and the background noise in the raw sEMG data, we incorporated this signal-conditioning step prior to MAO detection as suggested in [26].

The remainder of the article is organized in the following manner. Section II-A renders an overview of the techniques deployed to preprocess the raw sEMG signals recorded from the

muscles of interest. The *scree-plot-based method* that mandates the estimation of an onset threshold has been derived in Section II-B, and the proposed profile likelihood maximization (PLM) algorithm is presented in Section II-D. The description concerning the variants of the threshold-based approach and those of the PLM is provided in Section II-C and II-E, respectively. Note that these variants and four other state-of-the-art strategies¹ have been implemented to validate the merits offered by the PLM, which is tailored to handle non-Gaussian sEMG data. The details of the actual as well as the simulated sEMG dataset provided in [1] and the derivation of an MAO *gold standard* are outlined in Section III-A. The quantitative results from the onset estimation techniques and the outcome of *Wilcoxon rank-sum test* to verify the statistical significance of the improvement offered by a scheme over another are consolidated in Section III-B; the behavior of PLM subject to noisy conditions is explored in Section III-C. Finally, suitable conclusions are drawn in favor of PLM variants founded on heavy-tailed distributions with pointers to future research directions in Section IV.

II. MUSCLE ACTIVATION ONSET DETECTION

We present two unsupervised methods for detecting MAOs from sEMG signals in the sequel. As mentioned earlier, prior to supplying the segments of sEMG data that contain both the background noise and the muscle activation to an MAO detection algorithm, the raw sEMG data segments are preconditioned with the TKEO. The first approach built around the scree-plot does make use of a threshold to designate all voltage data points considered to represent instances of muscle firing, and graphically represents the cumulative sum of all such occurrences. A change in the firing rate and/or recruitment of motor units inducing a change in the level of muscle activity is then detected by the appearance of a discontinuity in the scree-plot. Notwithstanding the requirement for threshold determination, this algorithm enjoys the following merits: it is simple to implement; the underlying principle is quite intuitive; and one of its variants, namely, SPE-RefineElbow, yielded comparable results with the PLM-Laplacian in experiments. On the other hand, unlike most of the MAO detection schemes, the second approach relying on the estimation of profile likelihood obviates the need for manual tuning of parameters, thereby overcoming the inherent limitation of an algorithm based on a muscle activation threshold.

A. sEMG Preprocessing

Since its introduction by Kaiser [34], the non-linear TKEO has been applied extensively to detect abrupt changes in broadband biological signals, e.g., spike detection of neurological signals as in [35]. Subsequently, Li *et al.* demonstrated that the TKEO could lead to more accurate EMG onset detection [25]. Premised on the findings in [26] and [36]—TKEO can be very effective when used in conjunction with an EMG onset detection scheme—we employ this technique for signal conditioning prior to supplying the EMG data to our MAO detection algorithm. In what proceeds, the definition of the TKEO operator is stated; for a more involved treatment on this topic, one may refer to [34].

¹Three variants of the BCD were compared, apart from three state-of-the-art algorithms.

Let us denote by $y[n]$ the samples of an sEMG signal pertinent to either muscle activations or baseline voltage. According to Kaiser in [34], a good measure of the energy of that signal can be elicited by the discrete TKEO²:

$$r(y[n]) = \tilde{p}[n] = y[n]^2 - y[n+1]y[n-1]. \quad (1)$$

The TKEO operator gained much popularity in the context of online sEMG preprocessing for the following reasons: (i) It is simple to implement as the expression in (1) involves only two multiplications and a sum. (ii) It is apparent from (1) that the energy estimate from the TKEO is independent of the initial phase [37]. (iii) It is derived from the instantaneous amplitude and frequency of the signal, which justifies its application to analyze the muscle activity, because the depolarization of a muscle cell membrane during a contraction produces rapid fluctuations in the amplitude and frequency of the signal [26]. (iv) Importantly, as its formulation is grounded on the properties of *motor unit action potentials* (MUAPs), i.e., amplitude and frequency, it tends to improve the SNR and hence the accuracy of onset detection [38].

Also worth mentioning is that the scree-plot based method and the PLM variant built around a one-sided distribution with positive real line support require the TKEO to be rectified, which is realized by taking the absolute value of (1). Note that prior to conditioning the sEMG data by the TKEO, the raw data has been supplied to a second-order lowpass (LP) filter with the high cut-off frequency of 60 Hz, which would eliminate the high frequency noise [39]. The raw sEMG data acquired from the *extensor digitorum* (ED) muscle during a hand-grip task, the LP filter output, and the TKEO-conditioned signal are displayed in Fig. 1.

B. Scree-Plot-Based MAO Detection

Threshold-based MAO detection algorithms were popularized in [39], which require to preset a threshold value to predict the data point associated with the MAO. Given the mean μ_{baseline} and the standard deviation (SD) σ_{baseline} of the amplitude of data points that constitute the baseline of the TKEO-conditioned sEMG signal, the threshold Γ is more commonly deduced as:

$$\Gamma := \mu_{\text{baseline}} + h\sigma_{\text{baseline}} \quad (2)$$

where the parameter h ought to be determined within a reasonable range, e.g., 3, [6 8], and 15 as propounded in [40], [25], and [39], respectively. Note that the choice of h for a specific sEMG dataset is contingent on the magnitude of the baseline relative to that of muscle activities in the aforementioned works. Any substantial variation in baseline or muscle

²In the classical signal processing literature, the first term in the TKEO operator $y[n]^2$, which takes into account the signal amplitude, measures the *instantaneous energy* of a signal, and hence referred to as the *squared energy operator*. Notice that the TKEO has an additional term that accounts for the frequency of a signal as can be inferred from its derivation. This is a remarkable trait when it comes to time series analysis.

contraction activities could lead to erroneous MAO detection. As opposed to these strategies, whose performance would be dictated by the value of h , the *scree-plot elbow detection* scheme (SPE) deploys the threshold merely for the sake of marking and quantifying the level of muscle activities, and seeks for a relative change in the sEMG amplitude as shown in Fig. 2, thereby making it more robust to trial-to-trial variation in the muscle contraction and activity. This in turn permits some leeway for deciding on the parameter value without compromising the accuracy.

In this pursuit, the amplitude of TKEO-conditioned and rectified sEMG data points characterizing the baseline and muscle activities,

$$p[n] := |\tilde{p}[n]|, \quad n = 1, 2, \dots, N \quad (3)$$

is thresholded using (2) with $h = 4$

$$\widetilde{p}[n] = \begin{cases} 1 & \text{if } p[n] \geq \Gamma \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

as illustrated in Fig. 3 (a) and (b). Even though we implement the scheme with a fixed value of h in the preliminary investigations, one can have the freedom to select h within a wider interval— $h \in [3 \ 7]$ is permissible surmised on the empirical evidence that the onset detection accuracy is not adversely affected by the parameter tuning. Next, the cumulative sum of the threshold crossings

$$q[n] = \sum_{i=1}^n \widetilde{p}[i], \quad n = 1, 2, \dots, N \quad (5)$$

is computed for the preprocessed sEMG data; upon plotting, it would resemble a scree-plot with a sharp elbow point as portrayed in Fig. 3 (c)–(e). From a statistical viewpoint, a “gap” in the scree-plot suggests that the data on either side of the elbow point follow disparate distributions. In the physiological sense, the elbow point reflects a change in the muscle activity, i.e., an increase in the motor unit firing frequency or recruitment. As a consequence, the MAO detection turns out to be equivalent to estimating the position of the elbow point in the scree-plot of threshold crossings. Toward this, an intuitive approach built on *piecewise* or *segmented regression* is recommended in this framework, whose implementation subtleties are presented in Algorithm 1. In principle, one traverses along the curve, and selects one bisection point at a time for performing two linear regressions in a manner described below. The first line segment is constructed with an intent to provide the best fit for the series of points to the left of the bisection point; likewise, the second one accounts for the points to the right (see Fig. 3 (c)–(e)). As illustrated in Fig. 3 (f), the bisection point that minimizes the sum of errors for the two linear fits, thereby representing the best fit, would fall at the elbow of the scree-plot and hence is regarded as the data point index pertaining to the MAO. This segmented regression problem is formulated as

$$\arg \min_k \sum_{i=1}^k [b_i - (\beta_0 + \beta_1 a_i)]^2 + \sum_{i=k+1}^N [b_i - (\gamma_0 + \gamma_1 a_i)]^2 \quad (6)$$

where the x - and y -coordinates of $q[1], q[2], \dots, q[N]$ are denoted as $(a_1, b_1), (a_2, b_2), \dots, (a_N, b_N)$, respectively; the coefficients β_0 and β_1 denote the y -intercept and slope of the trend line that best represents the points to the left of the bisection point $k, (a_i, b_i), \forall_i \leq k$, respectively, whereas γ_0 and γ_1 are the corresponding coefficients in the equation of the linear regression line constructed with the points to the right of $k, (a_i, b_i), \forall_i > k$.

C. Variants of SPE-MAO

A few variants of the SPE-MAO algorithm have been implemented, wherein the candidate MAO data point index $\hat{k}$ returned by Algorithm 1 is either fine-tuned based on some criteria or modified with another approach.

SPE-MultiThresholdElbow: We recollect that the performance of SPE-MAO algorithm is not heavily reliant on a specific value of h in step 2, contrary to naïve threshold-based approaches, which allows one to relax the choice of h within a meaningful range and to explore the outcome. Based on this motivation, the parameter h in (2) is assigned a value in the set $\{3, 3.5, \dots, 5\}$ in each run, and $\hat{k}$ is determined to be the rounded average of the MAO indices estimated by the trial executions.

SPE-RefineElbow: In practical instances, $\hat{k}$ estimated by Algorithm 1 tends to fall a few milliseconds past the initiation of muscle activation. To counteract this effect, the following expedient is adopted: each TKEO-conditioned sEMG data point belonging to the set, $\{p[\hat{k} - \tau], p[\hat{k} - \tau + 1], \dots, p[\hat{k} - 1]\}, \tau \in \mathbb{N}^+$, is sequentially verified whether its amplitude exceeds the threshold defined in (2), until a data point complies with this criterion for its index to be designated as $\hat{k}$. In other words, the refined elbow index would satisfy the condition

$$q[\hat{k}] > q[\hat{k} - 1]$$

thereby ascertaining that the estimated MAO coincides with a muscle firing.

SPE-PolySmoothElbow: We conjecture that the SPE-MAO detection accuracy may further be enhanced if the points, $q[n], n = 1, 2, \dots, N$, are slightly altered to lie on a smooth curve, supposedly because the flex in the resulting scree-plot would be more distinct. With this intent, the scree-plot comprising $q[n]$ is replaced by a smooth curve generated using the polynomial of degree 10 that would fit $q[n]$ best in a least-squares sense. Upon inputting the data points that constitute this curve, Algorithm 1 finds the index $\hat{k}$.

D. Profile-Likelihood-Based MAO Detection

As dealt with in Section II-B, the preconditioned sEMG data points on either side of the elbow point in the screeplot can be regarded as samples drawn from two different distributions, representing different levels of muscle activity. Therefore, it is more fitting to recast the MAO estimation problem within a stochastic framework. More formally, a statistical model is constructed by hypothesizing that the ordered sEMG data points preconditioned with the TKEO operator belong to two different distributions. This means that if it is feasible to estimate the index k such that the set of data points, $S_1 = \{\tilde{p}[1], \tilde{p}[2], \dots, \tilde{p}[k]\}$, represents the baseline activities such as noise, and the set containing the remaining data points, $S_2 = \{\tilde{p}[k+1], \tilde{p}[k+2], \dots, \tilde{p}[N]\}$, implies the muscle activation, then it is more likely that the data points under these two categories are governed by two dissimilar PDFs. Based on this supposition, S_1 and S_2 can be construed as independent samples drawn from the distribution $f(\tilde{p}; \psi_1)$ and $f(\tilde{p}; \psi_2)$, respectively. Hence, the objective of the PLM algorithm boils down to robustly estimating the value of k by way of maximizing the likelihood function $\mathcal{L}(k, \psi_1, \psi_2)$.

The original PLM algorithm was propounded by Zhu and Ghodsi in [41], whose efficacy has been demonstrated in a potential application—automatically selecting the dimensionality, subsequent to decomposing a multivariate dataset with the *principal component analysis*. In the present setting, this algorithm has been tailored to estimate the MAO by modeling the presumably non-Gaussian sEMG data with suitable density functions, such that the maximum of the resulting likelihood function would point to the occurrence of a muscle onset.

For the sake of simplicity, suppose that the likelihood function depends only on two parameters—main parameter of interest k and a nuisance parameter ψ . An attempt to maximize $\mathcal{L}(k, \psi)$ would be unarguably more involved. This setback can however be mitigated by resorting to the profile likelihood approach, which will estimate the parameters in two stages. First, the likelihood function for a fixed k , i.e., $\mathcal{L}_k(\psi)$, is represented as a curve over ψ . Second, by evaluating the maximum $\mathcal{L}_k(\psi)$ over ψ , and choosing the k that yields the maximum over all these curves, an estimate of k is arrived at. Phrased differently, we evaluate

$$\hat{k} := \arg \max_k \mathcal{L}_k(\hat{\psi}_k) = \arg \max_k \mathcal{L}(k, \hat{\psi}_k)$$

Where $\hat{\psi}_k$ is nothing but the *maximum likelihood estimate* (MLE) of ψ for a fixed k . As the name implies, the likelihood function $\mathcal{L}_k(\hat{\psi}_k)$ is expressed merely in terms of the parameter of interest k , and the nuisance parameter ψ is *profiled* out. In a statistical sense, the maximization of profile likelihood is thus tantamount to picking a value for k that maximizes the *log-likelihood* function built upon the hypothesis that the sEMG data points stem from two distinct distributions.

Regardless of the fact that the profile likelihood may not be deemed as a proper likelihood function, in the sense that its first derivative does not have zero mean, it is an attractive

alternative in light of maximization due to the rationale that follows. (i) While the availability of *marginal* and *conditional likelihoods* is limited to very special problems, the profile likelihood is guaranteed to exist always [42], [43]. (ii) The estimate of a parameter via profile likelihood turns out to be its MLE, meaning that the use of profile likelihood in the point estimation³ context is well supported. For further reading on the pros and cons of the profile likelihood approach, one may refer to [42] and [43].

Before delving into the algorithmic details, the fundamental differences between the original algorithm in [41] and the adapted version are stated below.

1) Amongst a collection of distributions with an infinite support, i.e., $(-\infty+\infty)$, we opted for the Laplace PDF on the basis of empirical evidences that show that the preconditioned sEMG data points $\tilde{p}[n], n = 1, 2, \dots, N$, recorded from several muscles seem to reasonably follow the Laplace distribution. For instance, the histogram with a distribution fit illustrated in Fig. 4 and the *quantile-quantile* (Q-Q) plot in Fig. 5 validate whether the distribution of TKEO-conditioned sEMG data collected from the ED muscle in the course of a hand-grip task can reliably be approximated to a Laplace one. We remark that the accuracy of the MAO detection scheme has significantly been improved by this PDF choice in our experiments. Recall that the TKEO-conditioned and rectified sEMG data points $p[n]$ are on the other hand positive-valued (refer to the bottom row of Fig. 1). Consequently, a distribution supported on the whole real line is clearly not suitable for the treatment of the rectified data points. Instead, one must select a distribution from the family of PDFs supported on the semi-infinite interval, $[0+\infty)$, e.g., the *log-normal* distribution is a judicious choice.

2) In contrast with the algorithm derived in [41] that employs a common *scale parameter* $\hat{\sigma}$ for both samples, S_1 and S_2 we prefer to work two distinct scale parameters, $\hat{\sigma}_1$ and $\hat{\sigma}_2$ each one associated with the Laplace distribution the data that represent the baseline activities and the muscle activation, respectively.

What follows is the formal description and the statement of the PLM-MAO detection algorithm. Under the independence assumption, the log-likelihood function can be given by

$$\mathcal{L}(k, \psi_1, \psi_2) = \sum_{i=1}^k \log f(\tilde{p}[i]; \psi_1) + \sum_{j=k+1}^N \log f(\tilde{p}[j]; \psi_2). \quad (7)$$

The profile likelihood for a chosen value of k can be derived by plugging in the MLEs of ψ_1 and ψ_2 that are obtained from S_1 and S_2 respectively into, (7):

³In statistics, the point estimation refers to calculating a single value by making use of sample data, which would serve as the “best estimate” of an unknown (fixed or random) population parameter.

$$\mathcal{L}_k(k) = \sum_{i=1}^k \log f(\tilde{p}[i]; \hat{\psi}_1(k)) + \sum_{j=k+1}^N \log f(\tilde{p}[j]; \hat{\psi}_2(k)). \quad (8)$$

Note that in (8), the MLEs of ψ_1 and ψ_2 are denoted as functions of k so as to imply that these estimates rely on k . As advocated in [41], an exhaustive search is invoked that evaluates $\mathcal{L}_k(\iota)$, $\iota = 1, 2, \dots, N$, and the value of ι for which (8) attains the maximum is regarded as the estimate of k . In other words, the estimate of k can be defined as

$$\hat{k} := \underset{\iota = 1, 2, \dots, N}{\operatorname{argmax}} \mathcal{L}_k(\iota) \quad (9)$$

For instance, Fig. 6 illustrates the correspondence between the maximum of (8) and the onset of the ED muscle in a hand-grip trial. As emphasized above, owing to the nature of the TKEOconditioned sEMG data at hand, the Laplace distribution is considered suitable for the design of MAO detection algorithm. In view of this, the PDFs are expressed as

$$f(\tilde{p}; \mu_l, \sigma_l) = \frac{1}{2\sigma_l} \exp\left(-\frac{|\tilde{p} - \mu_l|}{\sigma_l}\right), \quad l = 1, 2$$

with μ_l and σ_l being the *location* and scale parameter—sometimes referred to as the *diversity*—respectively. Besides, the MLEs for μ_l and σ_l , $l = 1, 2$, corresponding to a given k are in order for completeness sake:

$$\hat{\mu}_1 = \text{sample median of } S_1 \quad (10)$$

$$\hat{\mu}_2 = \text{sample median of } S_2 \quad (11)$$

$$\hat{\sigma}_1 = \frac{\sum_{\tilde{p}[i] \in S_1} |\tilde{p}[i] - \hat{\mu}_1|}{k} \quad (12)$$

$$\hat{\sigma}_2 = \frac{\sum_{\tilde{p}[j] \in S_2} |\tilde{p}[j] - \hat{\mu}_2|}{N - k}. \quad (13)$$

Now we can set out to enunciate the step-wise implementation of the PLM-MAO scheme in Algorithm 2.

E. Variants of PLM-MAO

In order to assess the influence of the chosen PDF on the performance of the PLM-MAO algorithm, two more distributions have been investigated.

- **PLM-Gaussian:** In line with the algorithm in [41] and [22], a PLM-MAO algorithm can be derived by replacing the PDF and the respective parameter estimates in steps 3–6 of Algorithm 2 with those of Gaussian distribution as summarized in Table I.
- **PLM-LogNormal:** Since the preconditioned sEMG data seem to follow a Laplace distribution (also known as *double-exponential distribution*) as shown in Fig. 4, whose tails are heavier than a *standard normal*, another implementation has been carried out with the log-normal distribution characterized by heavy tails. Nonetheless, this distribution is supported only on the positive real line, thereby requiring the rectified TKEO-conditioned data as the input for the algorithm. In this respect, the PDF and the related statistics are listed in Table I.

III. RESULTS AND DISCUSSION

A. sEMG Dataset, Gold Standard, and Simulations

For investigating the performance of the proposed and the state-of-the-art algorithms, we have selected the sEMG dataset provided in [1] (<https://github.com/TenanATC/EMG>) and generated a simulated dataset as described in the article. The experimental protocol for the data collection, the derivation of MAO gold standard, and the procedure for creating a simulated dataset are detailed in [1], pp. 3 and 4. Yet we have recapitulated below a few technical details for the sake of completeness. Eighteen participants (13 male and 5 female of 33.3 ± 9.2 years) performed knee extension and elbow flexion of the right limb. Every individual repeated each task three times at a self-selected pace with a rest period of at least 60 s. Hence it resulted in a collection of 103 usable sEMG signals. The knee extension movement was performed while a mass of 2.3 kg was attached to the ankle of the subjects seated in a stationary chair. During the elbow flexion movement, a 2.3 kg mass was attached to the wrist of the participants seated in a chair with their elbow supported at 90° of flexion. The sEMG electrodes—Ag/AgCl, circular 10 mm diameter, 35 mm interelectrode distance, $>100 \text{ M}\Omega$, 95 dB CMRR, and 10 Hz–3.13 kHz bandwidth—were attached to the *vastus lateralis* (VL) and *biceps brachii* (BB) during the knee extension and elbow flexion, respectively. The electrode placed on the subject's ipsilateral *patella* served as a ground. The acquired signals were pre-amplified with a gain of 330 and then analog-to-digital converted at 2048 Hz.

Three researchers visually inspected the bandpass-filtered (10 to 1000 Hz) sEMG signals, and annotated the MAOs in a randomized and double-blind fashion meaning that the study identifier and the movement were unknowns. Each researcher detected the onset twice in every trial with a time gap of one to seven days. The reliability between and within the researchers were measured by the *intraclass correlation coefficient*, whose values are 0.88 and 0.92, respectively. The gold standard of the MAOs was determined to be the mean of the six visual markings.

The procedure for creating the simulated sEMG data for validating the MAO estimation algorithms is given in [1], p. 4, by which we generated 103 signals with artificial onsets, whose occurrences are precisely known. First, a fixed length of data prior to muscle contraction was extracted during when the muscle was always quiescent. Next, the baseline data was fused with the active sEMG, i.e., data succeeding the gold standard after a fixed time interval t ; in practice, t can be determined based on the largest visual onset deviation from the gold standard. Thus, discarding the sEMG data for a specified duration immediately after the gold standard would ensure that the muscle activation data does not contain any traces of baseline. The onset in simulated EMG is objective; on the other hand, the data series possesses an artificially profound onset as it is bereft of the gradual orderly recruitment of different motor units [1].

B. Performance Comparison of MAO Detection Algorithms

The mean, SD, median, and interquartile range (IQR)⁴ of errors were computed between the data sample indices associated with the MAOs according to the gold standard and each of the ten unsupervised methods—ScreePlotElbow (SPE), SPEMultiThresholdElbow (SPE-MTE), SPE-RefineElbow (SPERE), SPE-PolySmoothElbow (SPE-PSE), PLM-Laplacian (PLM-Lap), PLM-Gaussian (PLM-Gau), PLM-LogNormal (PLM-Log), WaveletChangeDetection (WCD), OnlyThreshold (OT), and three variants of BCD. While the PLM-Gau [41] and WCD [45]–[47] are widely recommended to solve a generic change detection problem, the OT [39] and BCD variants [1], [31] are devoted to the sEMG-based MAO detection. In a most recent and comprehensive experimental study, the BCD algorithm has been shown to have outclassed three established and two other statistical approaches (refer to Section I for details) [1], [31]. Parameter values to be set for the SPE variants are listed in Section II, and the BCD method was implemented as in [1]. In the WCD, the *maximal overlap discrete wavelet transform* is computed by means of *Daubechies extremal phase wavelet* with two *vanishing moments*⁵. It transforms the data down to level six and employs *reflection boundary handling* by extending the signal symmetrically at the right boundary to twice the signal length. Eventually the algorithm tracks two change points of the variance of the signal constructed with the wavelet coefficients obtained as mentioned above.

Table II reports the errors committed by each of the investigated algorithms in milliseconds. Overall, the PLM-Lap attained the most accurate MAO detection results in comparison with the rest of the approaches. Notice that the PLM-Log managed to yield comparable and slightly better results in simulations. Even though the WCD is a soughtafter scheme to address change detection problems, its performance significantly degraded presumably due to the muscle and baseline activities occluded with noise. The traditional OT technique warrants a more sophisticated mechanism to determine the parameter h in (2). In like manner, the PLM-Gau is apparently unsuitable for this application because the PDF of data representing either muscle or baseline activities does not conform to a Gaussian distribution (refer to Fig. 4). In spite of dedicated efforts to fine-tune the elbow point, the improvements

⁴The median and IQR describing the central tendency and spread, respectively, are also included to quantify the MAO detection errors resulted from various approaches, since they are robust against outliers and suitable for non-normal data.

⁵The higher the number of vanishing moments is, the smoother the wavelet will be.

offered by SPE variants over the naive SPE do not commensurate with computational overheads except in the case of SPE-RE. Recall from Section I that the reliability and accuracy of the BCD were reported to be at their best in [1] for the following hyperparameter settings: $p_0 = 0$, $\omega_0 = 0.2$, and posterior probability $\in [0.60, 0.95]$. Therefore, we tested three instances of BCD, namely, BAY60, BAY75, and BAY95, with the posterior probability set to be 0.60, 0.75, and 0.95, respectively, as well as $p_0 = 0$ and $\omega_0 = 0.2$ in all three cases by inputting the rectified sEMG data. The BCD is a Bayesian methodology that relies on the *Markov Chain Monte Carlo* (MCMC) models to estimate the posterior distribution, because, in most cases, it is impossible to evaluate the posterior distribution analytically. The MCMC is an iterative procedure, and the inherent limitation is that it needs an initial seed. In practice, the solution is obtained at a finite number of iterations, and hence the outcome depends on the initial seed generated by the random number generator. Owing to the stochastic nature of the algorithm—BCD results differ slightly between runs—each variant of the BCD was executed 20 times with the actual and the simulated dataset. Therefore, the tabulated errors are the mean values across all the trials. Noteworthy is that the PLM-Lap and PLM-Log have outperformed the BCD variants in every trial execution.

In order to verify whether the improvement offered by the PLM-Lap is statistically significant with respect to a competing approach, we conducted the Wilcoxon rank-sum test. It is a non-parametric alternative to the unpaired *t*-test for comparing two independent groups of samples. The ranksum test is safer from a statistical viewpoint, as it does not require that the samples follow a normal distribution. Since it is based solely on the order in which the samples from the two groups fall, it remains less sensitive to outliers and noise than the parametric tests [48]. The Wilcoxon rank-sum test statistic is given by the sum of the ranks for samples from one of the groups [49]. A difficulty would, however, arise in comparing the outcome of a BCD variant with the rest of the approaches that are deterministic, because the samples from 20 repeated trial runs of BCD form clusters. This means that one of the assumptions of the rank-sum test—*independence within samples*—is violated. Nevertheless, an extension of the rank-sum test was posited in [50] to deal with clustered samples, in which Rosner *et al.* introduced a corrected variance formula for the Wilcoxon rank-sum statistic (eqns. (13) and (14), pp. 1254 and 1255). We have adopted this modification in our test procedure for the instances where the statistical test involved the BCD variants. The rank-sum test results, i.e., the accepted hypothesis and *p*-value, for the simulated and actual sEMG dataset are concisely presented in Fig. 7 (a) and (b), respectively. If the MAO error produced by the method labeled in a row is statistically significantly lower than that of the method in a column (H_1 is true), the rectangular cell at their intersection is shaded; otherwise (H_0 is true) the cell is left blank. The respective significance levels are reported with the convention introduced by Fisher and Yates in [44]: no asterisk if $p > 0.05$; one asterisk if $0.05 > p > 0.01$; two, three, and four asterisks if $0.01 > p > 0.001$, $0.001 > p > 0.0001$, and $p > 0.0001$, respectively. We remark that the onset error due to the PLM-Lap is statistically significantly lower than all investigated approaches with the actual sEMG dataset and all except the PLM-Log method with the simulated dataset. Interestingly, the error incurred by the PLM-Lap and PLM-Log with both datasets are statistically significantly lower than that of the state-of-the-art algorithms—BCD variants, WCD, PLM-Gau, and OT.

A graphical representation of the onset error from the methods under evaluation, known as *jitter-box plot*, is provided in Fig. 8, where the box-and-whisker plot depicting the median and IQR of error is superimposed on jitters portraying the error distribution in one dimension without the data points being stacked atop each other. The plots shown in Fig. 8 (a) and (b) were obtained for the simulated dataset comprising 103 cases, whereas the remaining ones (in Fig. 8 (c) and (d)) correspond to the actual 103 sEMG signals to visually compare the performance of various schemes. The signed error jitterbox plots in Fig. 8 (a) and (c) are intended to illustrate the bias (average error) and the spread around the median in a more qualitative sense; moreover, the whiskers will help notice the outliers from the respective methods. Complementarily, scrutinizing the mean and median absolute error in Fig. 8 (b) and (d) will enable one to readily assess the approaches. We refrain from including the whiskers, which by definition must be symmetric, in the absolute error jitter-box plots due to the highly skewed distribution of the absolute error. It is noticeable from Fig. 8 (a) and (c) that the errors from the SPE-RE, PLM-Lap, PLM-Log, and BCD variants have relatively lower bias, but most importantly, the spread—as reflected by the IQR—is conspicuously the lowest in the PLM-Lap.

C. Behavior of PLM-Lap Under Noisy Conditions

The onset detection strategies relying on the amplitude of the sEMG data, which is susceptible to noise, would inherently encounter difficulties as the SNR declines. Because of this limitation, statistical approaches tailored to estimate the onset do face challenges under noisy conditions. An attempt has therefore been made to learn the behavior of the PLM-Lap fed with sEMG signals contaminated by various degrees of noise. Given a simulated signal, a zero-mean white Gaussian noise (WGN) having the same length as that of the signal was generated. The SD for the noise-generator function was deduced by multiplying the maximum absolute baseline amplitude with a percentage selected from the set {1, 5, 10, 30, 50, 100, 200, 300}. The signal corrupted with an additive WGN (AWGN) was then obtained by point-wise addition of the signal and noise time series, which in turn was supplied to the PLM-Lap to predict the onset. For a simulated signal and a noise percentage, 20 noisy signals were thus produced that would be dissimilar due to the pseudorandom noise-generation process; the error due to algorithmic onset estimation was measured in each instant. The mean and median of the onset absolute error across 103×20 instances were plotted for each noise percentage in Fig. 9 (a) along with the scatter of the actual error. The curve interpolating the mean or median error alludes to an increasing linear trend for the onset error as the noise level escalates. The mean SNR values—per the definition⁶ in [1], p. 6—were also calculated for the set of 103×20 AWGN-corrupted signals pertaining to each noise percentage. The curves shown in Fig. 9 (b) are meant to infer how the mean or median absolute error would be influenced as the mean SNR of the noisy input for the PLM-Lap is varied. The jitters superimposed on the line plot in Fig. 9 (b) were simplified to enhance the interpretability by assigning the mean SNR associated with a noise percentage to the abscissa of each data point instead of the actual SNR. The IQR of the absolute onset error

⁶The SNR of an sEMG signal is defined as the ratio between the maximum amplitude during the muscle activation and the maximum amplitude of the baseline (or “quiet” EMG).

for each noise percentage or mean SNR is indicated in Fig. 9 using a rectangular box to express the spread of the error.

D. Discussion

Essentially the sEMG can be treated as cumulative additions of a series of MUAPs with various amplitudes and frequencies outracing some background non-physiological noise. Any enhanced sEMG activity would reflect an increase in the firing rate or recruitment of motor units, or both. The capability of an algorithm to detect a change in the activity is thus dependent on the amplitude of change beyond the noise level, the consistency among those changes across contractions, and the abruptness and magnitude with which the change occurs.

Based on our empirical findings, the OT is inherently unadaptable to trial-wise variability in the sEMG. Whereas, the scree-plot-based approach could resolve that issue by tracking only the changes in activity that exceed a certain threshold, and hence remains more robust to variations in sEMG activity changes. Nevertheless, its performance would degrade when the change is sluggish and at instances when the scree-plot fails to be approximated by straight lines around the MAO. To outweigh this shortcoming, several variants were attempted that yielded varied levels of success. Even though the WCD is widely applied to address a generic change detection problem, as remarked in Section III-B, it offered inconsistent results with noisy sEMG data. Recently published statistical methods— PTM [23] and BCD [1], [31]—are attractive alternatives. However, one needs to optimally tune various parameters of such methods to achieve desirable outcome. For instance, the PTM requires the setting of several parameters according to the sampling rate of the sEMG data. The BCD was claimed to produce the best result for the posterior probability selected within [0.60 0.95] in [1], whereas the study reported in [31] preferred the interval to be [0.85 0.95]. By contrast, PLM variants neither necessitate any *a priori* assumption on the type of sEMG change nor do they require parameter tuning.

IV. CONCLUSION AND FUTURE PERSPECTIVES

In an empirical study involving ten unsupervised statistical approaches, the PLM-Lap has been shown to accurately predict the onset of muscle activations from 103 sEMG signals given in [1] and 103 simulations with known onsets. The state-of-the-art and the advocated techniques have been quantitatively compared, and the performance improvement by the PLM-Lap has been verified by the Wilcoxon rank-sum test.

Future research directions are: (i) extending the investigation with the sEMG data subject to various percentages of *maximum voluntary contraction*; (ii) detecting changes in the muscle activity between two different contraction levels; and (iii) validating the algorithm with sEMG data collected from diverse experimental settings. For instance, hand muscles engaged during hand-grip trials are *flexor digitorum profundus* and *first dorsal interosseous*; targeted muscles in a plantar ankle flexion task are *medial* and *lateral gastrocnemius* as well as *medial* and *lateral soleus*; sEMG data from *tibialis anterior*, VL, and *rectus femoris* are germane to a forward balance task. An ambitious goal would be to evaluate whether the

PLM-Lap or PLM-Log is efficient in tracking the MAOs during a dynamic functional task, such as gait.

Recall that the onset estimation error is highly dependent on the derivation of the gold standard. Nevertheless, as the MUAP duration is typically in the order of 5 to 20 ms [51], any method performing within 10 to 25 ms accuracy would be sufficiently accurate for most purposes. What may well distinguish the methods is, how robust the performance is when faced with challenging conditions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Algorithm 1 SPE-MAO

input: an sEMG data segment, $y[n]$, $n = 0, 1, \dots, N + 1$, describing baseline and muscle activities

output: the sEMG data point index $\hat{k}$ pertinent to the MAO

- 1: Perform LP filtering, precondition the filter output with the TKEO, and rectify the resulting data to produce $p[n]$, $n = 1, 2, \dots, N$ $\triangleright$ stated in (3)
- 2: Deduce the threshold Γ with $h = 4$ $\triangleright$ defined in (2)
- 3: Construct the time series of thresholded data $p[n]$, $n = 1, 2, \dots, N$ $\triangleright$ according to (4)
- 4: Compute the cumulative sum of thresholded data to form $q[n]$, $n = 1, 2, \dots, N$ $\triangleright$ given in (5)
- 5: **for** $k = 1, 2, \dots, N$ **do**
- 6: Select k as the bisection point of the scree-plot
- 7: Estimate the *segmented regression error* (SRE) for

$$k \triangleright \text{SRE} := \sum_{i=1}^k [b_i - (\beta_0 + \beta_1 a_i)]^2 + \sum_{i=k+1}^N [b_i - (\gamma_0 + \gamma_1 a_i)]^2$$
- 8: **end for**
- 9: Pick the value of k that minimizes the SRE $\triangleright$ determined using (6)
- 10: **return** index $\hat{k}$ of the data point related to the MAO

Algorithm 2 PLM-MAO

input: an sEMG data segment, $y[n]$, $n = 0, 1, \dots, N + 1$, comprising baseline activities and the muscle activation

output: index $\hat{k}$ of the sEMG data point that corresponds to the MAO

- 1: Filter $y[n]$ with the second-order LP filter with $f_H = 60$ Hz
- 2: Condition the filtered signal with the TKEO to produce $\tilde{p}[n]$, $n = 1, 2, \dots, N$ defined in (1)
- 3: **for** $\iota = 1, 2, \dots, N$ **do**
- 4: Obtain the MLEs, $\hat{\mu}_1$, $\hat{\mu}_2$, $\hat{\sigma}_1$, and $\hat{\sigma}_2$ given by (10)–(13)
- 5: Evaluate the profile likelihood $\mathcal{L}_k(\iota)$ expressed in (8)
- 6: **end for**
- 7: Estimate the value of k according to (9)
- 8: return index $\hat{k}$ of the data point that pertains to the MAO

Fig. 1.

(a) Raw sEMG data (pink) recorded from the ED muscle during a hand-grip experiment. (b) The output of the LP filter—second-order Butterworth filter with $f_H = 60$ Hz—which was supplied with the sEMG data shown in (a). Notice that the filtered signal (orange) is devoid of high frequency noise as the LP filter annihilates the high frequency contents (> 60 Hz) from the raw sEMG. (c) The LP-filtered data was conditioned with the TKEO operator defined in (1), and subsequently rectified (green) to ensure that the energy operator output always remains positive. The threshold (Γ) deduced and the MAO detected by the scree-plot-based algorithm are marked with the horizontal (orange) and vertical (gray) line segment, respectively.

Fig. 2.

(a) Stem plot of the raw sEMG data (blue) acquired from the *flexor digitorum superficialis* (FDS) muscle during a hand-grip experiment. (b) Stem plot of the same data that has been LP filtered as well as TKEO-conditioned using (1) and then rectified. The amplitude threshold specified in (2) to select the MAO candidates is depicted with the horizontal line segment (orange), whereas the vertical line segment (gray) implies the data index that coincides with the MAO as returned by the SPE method.

Fig. 3.

(a) Stem plot (green) of an LP-filtered, TKEO-conditioned, and rectified FDS-sEMG data segment $p[n]$ for a period of 2 s, obtained during a hand-grip trial. (b) The thresholded data points $\tilde{p}[n]$ marked with asterisks (dark green) are stacked at two levels labeled as $> \Gamma$ and $< \Gamma$ to signify whether the magnitude of $p[n]$ is more and less than the set threshold Γ , respectively. (c) The SPE algorithm approximates the scree curve $q[n]$ (orange)—cumulative sum of $\tilde{p}[n]$ —with two linear regressions by fitting the set of points located to the left and right of a chosen bisection point depicted as a thick square. By dint of an exhaustive search, the algorithm finds the bisection point that results in the minimal sum of errors from both linear regressions as shown in dashed-dotted lines (black); this data point is deemed as the elbow point $\hat{k}$ delineated with a vertical line segment (gray). (d) & (e) By arbitrarily picking two incorrect elbow point candidates, whose indices are greater and smaller than $\hat{k}$, the piecewise linear regressors are graphically illustrated with two pairs of dashed-dotted lines (blue and olive green, respectively). (f) The regression error values are plotted as a function of n (purple) to accentuate that the minimum exactly coincides with $\hat{k}$.

Fig. 4. The histograms (olive green bars) of the preconditioned sEMG data—(a) baseline activities and (b) ED muscle activation—are fitted with Laplace distributions (orange curves). Visual inspection of these plots suggests that the PDF of the preconditioned sEMG data points may in general be approximated to a Laplace distribution.

Fig. 5.

Q-Q plots for the preconditioned sEMG data samples versus a Laplace distribution. Plot (a) corresponds to the sEMG baseline activities, whereas plot (b) concerns the ED muscle activation. Admittedly, a few outliers are evident at the extremes of both ranges. Otherwise, the preconditioned sEMG data fits the Laplace model reasonably well.

Fig. 6.

(a) Stem plot of the LP-filtered and TKEO-conditioned sEMG data (heliotrope) recorded during a hand-grip experiment from the ED muscle, where the MAO detected by the PLM-Laplacian method is marked by a vertical line segment (gray). (b) The profile likelihood defined in (8) is plotted as a function of time (orange); observe that the time instant at which the function reaches the maximum is reckoned as the time of MAO occurrence as in (9).

	PLM-Lap	PLM-Log	BAY60	BAY75	SPE-RE	SPE	SPE-MTE	OT	BAY95	SPE-PSE	WCD	PLM-Gau
PLM-Lap			****	****	****	****	****	****	****	****	****	****
PLM-Log			****	****	****	****	****	****	****	****	****	****
BAY60				****	**	****	****	****	****	****	****	****
BAY75						**	**	**	****	****	****	****
SPE-RE									*	*	****	****
SPE											****	****
SPE-MTE											***	****
OT											****	****
BAY95											****	****
SPE-PSE											***	****
WCD												
PLM-Gau												

(a)

	PLM-Lap	PLM-Log	BAY60	BAY75	SPE-RE	SPE	SPE-MTE	BAY95	SPE-PSE	WCD	OT	PLM-Gau
PLM-Lap		*	****	****	***	****	****	****	****	****	****	****
PLM-Log						*	*	**	**	****	****	****
BAY60						*	*	****	****	****	****	****
BAY75								****	**	****	****	****
SPE-RE									*	****	****	****
SPE										****	****	****
SPE-MTE										****	****	****
BAY95										****	****	****
SPE-PSE										****	****	****
WCD												
OT												
PLM-Gau												

(b)

Fig. 7.

The outcome of Wilcoxon rank-sum test to validate whether the MAO error produced by an algorithm specified in a row is statistically significantly lower compared to each of the remaining 11 algorithms in the columns. All the 12 experimented algorithms were supplied with (a) 103 simulated signals with known onsets and (b) 103 sEMG signals recorded from VL and BB muscle during the knee extension and elbow flexion, respectively. If the error happens to be statistically significantly lower, the rectangular cell located at the intersection of the respective row and column is shaded (teal) to imply H_1 is true; otherwise, the cell is left empty meaning H_0 is true. The significance level for a pair of tested algorithms is marked according to the asterisk convention followed by Fisher and Yates in [44]: no asterisk if $p > 0.05$; one asterisk if $0.05 > p > 0.01$; two, three, and four asterisks if $0.01 > p > 0.001$, $0.001 > p > 0.0001$, and $p > 0.0001$, respectively.

Fig. 8.

Jitter-box plot is the superimposition of the box-and-whisker plot illustrating the bias (average error) and the spread of the error with the median and IQR (in ms), respectively, on the jitter plot that depicts the scatter of the actual error encountered by 12 MAO estimation algorithms. (a) Signed error and (b) absolute error in detecting onsets from 103 simulated signals by the algorithms under study. (c) Signed error and (d) absolute error due to algorithmically-estimated onsets from 103 sEMG signals collected during the knee extension and elbow flexion from VL and BB, respectively. The plots with the signed and absolute error provide complementary information. While the bias and the spread around the median can be qualitatively assessed with the signed error, the performance can be straightforwardly evaluated by comparing either the mean or the median absolute error. Note that the whiskers that help identify the outliers are provided only for the plots with the signed error owing to the requirement that they must remain symmetric.

Fig. 9.

The accuracy of onset estimation with a stochastic algorithm is adversely affected due to an AWGN that would considerably alter the amplitude of the sEMG data. The performance degradation of the PLM-Lap on account of possible noise contamination of the sEMG data was empirically analyzed using 20 noisy instances of 103 simulated signals for each of the eight progressively increasing noise levels. (a) The mean and median of the onset absolute error estimated from a set of noise-corrupted signals are plotted against the noise injected as a percentage of maximum absolute baseline amplitude. The line plot revealing an increasing linear trend for the onset error is superimposed on the jitters representing the actual error. (b) The mean and median absolute error versus the mean SNR value computed for each noise percentage. Notice that the abscissa of each point in the jitter plot has simply been assigned the mean SNR instead of the actual SNR to enhance the interpretability of the plot. The IQR of the absolute onset error for each noise percentage or mean SNR is shown using a rectangular box to indicate the spread of the error.

TABLE I

PARAMETER ESTIMATES OF SELECTED PDFs FOR IMPLEMENTING VARIANTS OF PLM-MAO ALGORITHM

Distribution	PDF	Location parameter	Scale parameter
Gaussian	$f(\tilde{p}; \mu_{\ell}, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left[-\frac{(\tilde{p} - \mu_{\ell})^2}{2\sigma^2}\right];$ $\ell = 1, 2$	$\hat{\mu}_1 = \frac{\sum_{\tilde{p}[i] \in s_1} \tilde{p}[i]}{k}$ $\hat{\mu}_2 = \frac{\sum_{\tilde{p}[j] \in s_2} \tilde{p}[j]}{N-k}$	$\hat{\sigma}^2 = \frac{(k-1)\hat{\sigma}_1^2 + (N-k-1)\hat{\sigma}_2^2}{N-2}, \text{ Where}$ $\hat{\sigma}_1^2 = \frac{\sum_{\tilde{p}[i] \in s_1} (\tilde{p}[i] - \hat{\mu}_1)^2}{k}$ $\hat{\sigma}_2^2 = \frac{\sum_{\tilde{p}[j] \in s_2} (\tilde{p}[j] - \hat{\mu}_2)^2}{N-k}$
Log-normal	$f(p; \mu_{\ell}, \sigma_{\ell}^2) = \frac{1}{\sqrt{2\pi}\sigma_{\ell} p} \exp\left[-\frac{[\ln(p) - \mu_{\ell}]^2}{2\sigma_{\ell}^2}\right]; \ell = 1, 2$	$\hat{\mu}_1 = \frac{\sum_{p[i] \in s_1} \ln(p[i])}{k}$ $\hat{\mu}_2 = \frac{\sum_{p[j] \in s_2} \ln(p[j])}{N-k}$	$\hat{\sigma}_1^2 = \frac{\sum_{p[i] \in s_1} (\ln(p[i]) - \hat{\mu}_1)^2}{k}$ $\hat{\sigma}_2^2 = \frac{\sum_{p[j] \in s_2} (\ln(p[j]) - \hat{\mu}_2)^2}{N-k}$

TABLE II

MEAN, SD, MEDIAN, AND IQR OF MAO DETECTION ABSOLUTE ERROR IN MILLISECONDS FOR THE INVESTIGATED ALGORITHMS. BOLD FACED VALUES INDICATE THE MOST ACCURATE DETECTION AMONG THE TESTED APPROACHES.

MAO detection algorithms	Absolute error due to MAO estimation in ms							
	sEMG with simulated MAO as described in [1]				sEMG dataset presented in [1]			
	Mean	SD	Median	IQR	Mean	SD	Median	IQR
SPE	66	94	29	[12; 80]	83	98	44	[13; 104]
SPE-RE	59	91	23	[6; 78]	77	96	42	[11; 94]
SPE-MTE	66	93	32	[12; 73]	83	98	42	[13; 104]
SPE-PSE	69	90	39	[13; 88]	90	94	65	[22; 124]
PLM-Lap	28	64	9	[2; 23]	46	81	21	[4; 46]
PLM-Gau	216	279	96	[30; 272]	273	325	161	[53; 329]
PLM-Log	26	60	7	[1; 23]	59	77	34	[6; 87]
WCD	179	181	109	[16; 375]	235	182	209	[70; 354]
OT	46	40	37	[13; 66]	204	138	178	[100; 272]
BAY60	39	59	19	[4; 56]	138	255	38	[8; 120]
BAY75	45	55	27	[8; 63]	115	203	39	[9; 119]
BAY95	61	66	41	[13; 86]	111	164	47	[10; 138]