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Analysis of Surface EMG Baseline for Detection of Hidden Muscle Activity

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Abstract

Objective—This study explored the feasibility of detecting hidden muscle activity in surface electromyogram (EMG) baseline.

Approach—Power spectral density (PSD) analysis and multi-scale entropy (MSE) analysis were used respectively. Both analyses were applied to computer simulations of surface EMG baseline with presence (representing activity data) or absence (representing reference data) of hidden muscle activity, as well as surface electrode array EMG baseline recordings of healthy control and amyotrophic lateral sclerosis (ALS) subjects.

Main results—Although the simulated reference data and the activity data yielded no distinguishable difference in the time domain, they demonstrated a significant difference in the frequency and signal complexity domains with the PSD and MSE analyses. For a comparison using pooled data, such a difference was also observed when the PSD and MSE analyses were applied to surface electrode array EMG baseline recordings of healthy control and ALS subjects, which demonstrated no distinguishable difference in the time domain. Compared with the PSD analysis, the MSE analysis appeared to be more sensitive for detecting the difference in surface EMG baselines between the two groups.

Significance—The findings implied presence of hidden muscle activity in surface EMG baseline recordings from the ALS subjects. To promote the presented analysis as a useful diagnostic or investigatory tool, future studies are necessary to assess the pathophysiological nature or origins of the hidden muscle activity, as well as the baseline difference at the individual subject level.

INTRODUCTION

Examination of spontaneous muscle activity is an important part of routine electromyogram (EMG), particularly in supporting the diagnosis of amyotrophic lateral sclerosis (ALS) and its variants [1–3]. The detection of both spontaneous motor unit activity (e.g. fasciculation potentials) and spontaneous muscle fiber activity (e.g. fibrillation potentials and positive sharp waves) can be conventionally achieved by needle EMG. Surface EMG can also be

used to detect spontaneous motor unit activity [4–7], while there is no clear evidence that fibrillation potentials can securely be detected in time domain signals recorded by surface electrodes. An earlier study using rat preparations [8] recorded EMG baseline of denervated muscles with conventional surface electrodes. It was found that fibrillation potentials from denervated rats are not readily discernible in the time domain, but can be clearly discerned in the frequency domain, evidenced by greatly increased energy in the frequency band of 100–300 Hz compared with normal rat data. The study suggested that surface EMG detection of fibrillation potentials may be feasible in other domains even when there is no distinguishable EMG activity appearing in the time domain.

In addition to fibrillation potentials, it is possible that other spontaneous or involuntary (or unintentional) muscle activity may be present in surface EMG baseline when recording from resting muscles of patients with neuromuscular diseases (e.g., ALS). For example, spontaneous or involuntary EMG activity from deep motor units is likely to be hidden in background noise. Similar to fibrillation potentials, such hidden activity is difficult to be observed in the time domain.

The objective of this study was to assess the feasibility of detecting the presence of hidden muscle activity in surface EMG baseline by applying signal processing techniques in the frequency domain and the nonlinear dynamic domain, respectively [9]. These include the conventional power spectral density (PSD) analysis as used in [8] and the more complicated multi-scale entropy (MSE) analysis [9]. The MSE analysis, which is a combination of the entropy analysis [10] [11] and the multi-scale approach, can quantify signal complexity or irregularity over different time scales. The MSE analysis has achieved many applications in assessing the nonlinear dynamic property of physiological signals, such as cardiac interbeat interval [12], fetal heart rate [13], pulse wave velocity [14], and laser Doppler flowmetry time series [15]. Recently, the MSE analysis has been used to characterize different spontaneous motor unit patterns, thus expanding the knowledge beyond what was previously obtained using conventional linear methods [16].

In the current study, both PSD and MSE analyses were performed on computer simulations of surface EMG baseline with presence or absence of hidden muscle activity. The former was modeled as a combination of hidden muscle activity and additive Gaussian white noise, representing activity data, whereas the latter was modeled as pure Gaussian white noise, representing reference data. These computer simulations allowed for a quantitative assessment of the PSD or MSE behavior with varying degrees of presence of hidden muscle activity. Furthermore, similar analyses were also applied to experimental surface EMG baseline recordings from healthy control and ALS subjects. The difference in PSD or MSE parameters between the two groups were examined with the view toward detecting the presence of hidden muscle activity in surface EMG baseline recorded from ALS patients.

METHODS

A. Computer Simulation of Hidden EMG Activity in Surface EMG baseline

A computer model as used in [8] was implemented to simulate hidden muscle activity recorded with a surface EMG electrode. The surface EMG recording of hidden muscle

activity was simulated as an electrical composite of action potentials from multiple origins. These would potentially include spontaneous action potentials from denervated muscle fibers, and those from involuntarily firing small/deep motor units as well. The action potential train from a specific origin can be modeled as:

$$p_i = b_i(t - I_{i,j}), \quad (1)$$

where i is origin index, b_i indicates the action potential function which varies with different origins, $I_{i,j}$ denotes the occurrence time of the j -th firing from the i -th origin. The firing of possible origins was expected to be independent. The occurrence time of the first firing for all the origins was simulated to have a uniform distribution in a range of 0–50 ms [8]. The inter-spike interval (ISI) is denoted as:

$$ISI_j = I_{i,j} - I_{i,j-1}, \quad j \geq 1, \text{ and } I_{i,0} = 0. \quad (2)$$

For the i -th origin, the ISI was assigned a normal distribution with a mean of $1/f$ and a standard deviation (SD) of $20\% \times 1/f$, where f represents the firing rate of the origin. The hidden muscle activity generated by multiple origins can be modeled as:

$$s(t) = \sum_{i=1}^N a_i \sum_j b_i(t - I_{i,j}) \quad (3)$$

where a_i is a scaling factor that accounts for the size and depth of an origin, and N is the number of active origins producing hidden activity. Assume that a surface electrode can detect the activity from up to $N_f = 2000$ different origins, another factor r_d was set between 0 and 1 to represent the rate of hidden activity. It follows that the number of origins generating the hidden activity can be determined as $N = N_f \times r_d$, and the resultant surface EMG baseline recording can be modeled as:

$$x(t) = w(t) + \delta \cdot s(t) \quad (4)$$

where $w(t)$ represents Gaussian white noise and the factor δ is used to adjust the level of hidden EMG, which determines the signal-to-noise ratio (SNR) defined as:

$$SNR = 10 \cdot \lg[\sum_t \delta^2 s^2(t) / \sum_t w^2(t)] \quad (5)$$

The SNR proposed in the model is used to roughly account for some factors that may affect the level of hidden EMG, such as thickness of the subcutaneous fat. Different levels of EMG activity can be simulated to be hidden in the background baseline by choosing appropriate SNR values.

In our model, the action potential waveforms were simulated by scaling the amplitude and duration of experimental fasciculation potential templates recorded from ALS subjects as shown in Fig. 1. The duration of the action potentials was distributed within a range of 6–24 ms. Table I summarizes the parameters assigned for the simulation.

Fifty segments of hidden muscle activity were simulated for a 2-s time duration with a sampling rate of 2 kHz. Fifty white noise segments of the same duration and sampling rate with a zero mean and a standard deviation of 1 μV were also simulated, representing surface EMG baseline without hidden muscle activity (denoted as reference group). A group of surface EMG baseline was obtained by combining simulated hidden muscle activity with the white noise (denoted as activity group). To evaluate the effect of different SNRs or activity rates on the PSD or MSE analysis, a series of activity group data were simulated by setting SNR at 10 dB, 0 dB and -10 dB respectively when the activity rate $r_d = 100\%$, and by setting activity rate r_d at 10%, 40%, 100% when the factor δ was fixed as the value yielding SNR = 0 dB at the activity rate of 100%. For each condition, 50 segments of data were generated. All simulated signals were processed with a fifth-order Butterworth band-pass filter setting at 20–500 Hz.

B. Experimental Data Recording

Experimental surface EMG baselines were processed in this study, which were taken from a database of spontaneous surface EMG recordings of 9 subjects (six males, three females, 57 ± 7 years) with “Definite ALS” or “Probable ALS with Laboratory Support”, as well as of 9 healthy control subjects (four males, five females, 45 ± 16 years). During the data collection, each subject was positioned comfortably supine on a clinical bed in a quiet examination room. While the tested arm was placed in its resting position, spontaneous surface EMG was recorded bilaterally from the thenar group muscles by a flexible surface electrode array (TMS International BV, The Netherlands) with 64 recording probes arranged in an 8×8 square matrix. Each recording probe has a contact surface of 1.2 mm in diameter and the center-to-center distance between two consecutive recording probes (in horizontal or vertical direction) is 4 mm. The recording for each muscle lasted for at least 3 minutes. The EMG signals were amplified by the Refa EMG system (TMS International BV, The Netherlands) with a reference electrode located on the olecranon (each channel had a feedback subtraction of the average of all the recording channels). The signals were recorded with a sampling rate of 2 kHz per channel and a bandpass filter setting at 20–500 Hz. All the experimental procedures were approved by local human studies committee.

All the recorded surface EMG data was imported to the Spike2 software (version 7.0; Cambridge Electronics Design [CED], Cambridge, UK). The signals were visually examined with the purpose of manually selecting the surface EMG baseline segments. A segment of baseline data consisting of all 64-channel time series was selected under the condition that there were no visible action potential spikes (e.g. fasciculation potentials) in each individual channel. Channels that suffered from noise interference (e.g. power line interference or motion artifacts) were excluded for further analysis. Fifty 2-s segments of surface EMG baseline were selected from the ALS database to form the ALS data group. Similarly, another fifty 2-s segments of surface EMG baseline were selected from database of the neurologically intact subjects to form the control group for comparison.

C. PSD Analysis

The PSD of both simulated data and experimental data was calculated with an augmented length of 4096 by zeros for fast Fourier transform (FFT). For experimental recordings, the

PSD result of each array data segment was obtained by averaging the spectral power across all the channels. Spectral power differences between the activity and reference data groups (from the simulation data), and between the ALS and control data groups (from the experimental data) were examined respectively, by calculating the average dB difference over a range of frequencies.

D. MSE Analysis

The MSE was introduced by Costa and colleagues [9] for quantifying the complexity of a signal, which calculates the entropy values over a wide range of time scales. The MSE algorithm usually consists of the coarse-grained process and the single-scale entropy calculation.

Given a time series of L points $x(t)$, $t = 1, 2, \dots, L$, a number of consecutive coarse-grained time series $y_\tau(s)$ are constructed, as a function of the scale factor τ .

$$y_\tau(s) = \frac{1}{\tau} \sum_{t=(s-1)\tau+1}^{s\tau} x(t), \quad s=1, 2, \dots, \frac{L}{\tau}, \quad (6)$$

where $y_1(s)$ is the original time series; L/τ is the length of each coarse-grained time series.

An entropy measure, either approximate entropy (ApEn) or sample entropy (SampEn), can be calculated for each sequence $y_\tau(s)$. The ApEn family parameters, which were introduced by Pincus [10], are appropriate for analyzing short, noisy time series, whereas the SampEn, which was originally proposed by Richman and Moorman [11] as a refinement of ApEn, has the advantage of being less dependent on the time series length. The SampEn is usually preferred in MSE analysis to quantify coarse-grained time series [12–15]. To compute SampEn, a scalar time series $\{y(s)|s = 1, 2, \dots, M\}$ is first embedded in a delayed m -dimensional space, where vectors are constructed as:

$$\mathbf{y}^{(p)} = [y(p+k)]_{k=0}^{m-1}, \quad p=1, 2, \dots, M-m+1 \quad (7)$$

The probability B that two sequences match for m points is computed by counting the average number of vector pairs, for which the distance is lower than the tolerance r . Similarly, A is defined for an embedding dimension of $m+1$. The SampEn is then calculated as:

$$\text{SampEn}(y, m, r) = -\ln(A/B) \quad (8)$$

One issue of SampEn calculation is to determine the dimension m and tolerance r . In this work, empirically we set $m = 2$ and $r = 0.15 \times \text{SD}$, the standard deviation of the original time series. For the MSE analysis, a number of time series $y_\tau(s)$ in different scales result in a series of SampEn values, which can be plotted as a function of the scale factor τ .

Similar to the PSD analysis, the MSE analysis of both simulated and experimental data was performed, with the scale factor ranging from 1 to 15. The MSE analysis of a single-channel data segment generated an MSE curve along a range of scale factors. For each experimental

data segment with multiple channels, the MSE results from all signal channels were averaged at every scale factor, to produce an average MSE curve. The MSE curves were compared between the activity and reference data groups (from the simulation data), and between the ALS and control data groups (from the experimental data).

E. Statistical Analysis

An unpaired t-test was used to examine whether there existed a significant difference in spectrum power over a certain frequency range between the activity and reference groups for simulation data, and between the ALS and control groups for experimental data, respectively. A two-way analysis of variance (ANOVA) was applied to the MSE results to examine the difference between groups as well, with the data group (activity or reference; ALS or control) and the scale factor (from 1 to 15) considered as both control factors. The significant level was set to be $p < 0.05$. All statistical analyses were performed using SPSS software (ver. 16, SPSS Inc. Chicago, USA).

RESULTS

Computer Simulation Results

1) Simulated Signals—Fig. 2 shows an example of surface EMG baseline simulation, in which (a) represents hidden muscle activity generated from 2000 origins, and (b) is Gaussian white noise. Fig. 2(c) and (d) are simulated surface EMG baselines by combining (a) and (b) at different SNRs. It can be observed that in the time domain it is difficult to discern any hidden muscle activity from the surface EMG baseline.

2) PSD and MSE Results at Different SNRs—Both PSD and MSE analysis results were reported as mean curves averaged over all 50 simulated surface EMG baselines for each of the reference and activity groups. These results derived from the surface EMG baseline with hidden activity at different SNRs are shown in Fig. 3. The activity rate was fixed at 100% (i.e. 2000 origins). As shown in the left panel of Fig. 3, the mean PSD of EMG baseline with hidden activity exceeded that of the pure background noise. The surface EMG baseline with higher SNRs yielded larger differences in spectral power over a certain frequency range between the two data groups. A frequency range of 30–120 Hz was considered, which was roughly estimated to be the frequency band with –3dB reduction (from the peak of PSD) at its lower and upper boundaries. The average dB difference between the two data groups over this frequency range was 5.29 dB, 9.29 dB and 13.92 dB at three levels of SNR (–10, 0, 10 dB), respectively, all with statistical significance ($p < 0.05$).

From the right panel of Fig. 3, it was observed that the activity and reference data groups generated different MSE curves. At scale factors 1 and 2, the reference data had higher entropy values than the activity data, indicating high complexity of white noise at such scales. The entropy value showed a descending trend with increase of scale factors for both reference and activity data groups. When the scale factor was larger than 4, higher entropy values were achieved with increase of SNR. Regardless of the SNR, the MSE curve for the reference data was below the MSE curves for the activity data at the scale factors of 4 and

larger ($p < 0.05$). Reducing the SNR of the activity data drove its MSE curve closer to that of the reference data.

3) PSD and MSE Results at Different Activity Rates—The PSD and MSE analysis results of simulated surface EMG baselines with different activity rates are shown in Fig. 4. In this analysis the SNR of the simulated signal was set to be 0 dB at 100% activity rate. Indeed, reduction of the activity rate would also decrease the SNR of the signal. Thus, similar to SNR changes, progressive decrease of the activity rate drove both the PSD and MSE results closer to those obtained from the reference data. The general power spectrum shape of the activity data was consistent across different SNRs or activity rates, as demonstrated by comparing the left panels of Fig. 3 and Fig. 4. The frequency range of 30–120 Hz was utilized to evaluate the dB difference between the two data groups, which was 2.48 dB, 5.60 dB and 9.29 dB at three levels (10%, 40% and 100%) of activity rates, respectively. The significance in difference was confirmed by the unpaired t-test ($p < 0.05$).

For the MSE analysis, when the scale factor was larger than 3, higher entropy values were achieved with increase of the activity rate. Regardless of the activity rate, the MSE curve for the reference data was below the MSE curves for the activity data. Reducing the activity rate drove the MSE curve of the activity data closer to that of the reference data. The ANOVA indicated that even at a 10% activity rate the MSE curve of the activity data still showed a significant difference from that of the reference data ($p < 0.05$).

Results of Experimental Signals

Two representative recordings of the surface EMG baseline from an ALS subject and a healthy control subject are shown in Fig. 5, where it was difficult to detect the difference of the two signals in the time domain. Fig. 6 shows the pool PSD and MSE analyses of the baseline recordings of ALS and healthy control subjects (The results were also reported as mean PSD and MSE curves averaged over 50 data segments in each data group), demonstrating a clear difference between the two groups. The PSD of the ALS data group was above that of the control data group in a frequency range of approximately 30–120 Hz. The PSD of each data group also showed multiple peaks due to 60 Hz power line interference and its higher harmonics. Because of this, the frequencies that were near (< 1 Hz) the 60 Hz and 120 Hz were excluded from the frequency range for the calculation of dB difference. Consequently, a significant difference of 2.9 dB (with a 95% confidence interval from 1.54 to 4.25 dB) was found between the two groups ($p < 0.05$).

The MSE curve derived from the control data group was similar to that of the computer-simulated white noise. The entropy values from the ALS data were lower than the control data for the first three scale factors, while an opposite trend was observed for the scale factors higher than 4. This pattern is analog to the MSE analysis of the simulated activity data. The ANOVA revealed a significant difference in entropy values between the two groups ($p < 0.05$ for all scale factors except 3 and 4).

DISCUSSION

Recent technical advances have been made in both surface EMG recording and processing, thus enhancing the utility of surface EMG [17–21]. This study presents a novel application of PSD and MSE analyses to surface EMG baseline processing for detection of hidden muscle activity. Compared with considerable efforts in detection of fasciculation potentials and other spontaneous or involuntary muscle activity clearly visible in time domain surface EMG recording [4–7], few efforts have been made toward detection of hidden muscle activity. Only one study was reported assessing the feasibility of fibrillation potential detection from spectral analysis of surface EMG baseline, using computer simulation as well as animal preparations [8].

Both PSD and MSE analyses were performed in this study using computer simulations of surface EMG baseline as well as experimental surface EMG baseline recordings from human subjects. We acknowledge that the simulations of hidden EMG activity in surface EMG baseline were created with a simplified computer model. For example, the low-pass filtering effect of the volume conductor was not thoroughly simulated, which was simply taken into account by scaling the amplitude and duration of experimental surface action potentials. The simplified computer simulation indicated that it was feasible to use PSD and MSE analyses to detect hidden muscle activity in surface EMG baseline recordings. Such feasibility was further confirmed by the significant difference in the power spectrum or the MSE curve between the ALS and match control subjects.

In general, the PSD difference revealed by the two groups in this study (i.e. the reference and activity groups for simulation data, and the ALS and control subjects for experimental data) showed a consistent pattern to the previous findings. We note that in [8] the frequency bandwidth of the hidden muscle activity (i.e. fibrillation potentials) was reported to be primarily within 100–300 Hz, whereas our study showed hidden muscle activity in surface EMG baseline within a frequency range of 30–120 Hz. Such a difference may be due to different volume conductor effects of the examined muscles in rats and human subjects.

In addition to the analysis of experimental surface EMG recordings of human subjects, the current study is characterized with several other features. Compared with conventional surface electrodes, high density surface EMG with an electrode array was used for the recording. The array electrode is constructed by a number of selective probes which can cover a large area of a muscle, and thereby enhance the chance of capturing hidden muscle activity in surface EMG baseline. The advantage of electrode array recording can be demonstrated by comparing the PSD analysis results derived from the array surface EMG recordings (Fig. 6) with those from a single EMG channel (Fig. 7), which was randomly selected from the array recordings for each data segment (while channels on muscle innervation zones were avoided). When only one channel of the array was used, it was likely that the PSD of the ALS data might not show a distinct difference from that of the control data. For example, as shown in Figure 7, the average dB difference within the same 30–120Hz frequency range between the two groups was 1.11 dB (with a 95% confidence interval from –0.21 to 2.44 dB) without statistical significance ($p = 0.10$). This observation

implies that large cover area of an electrode array can facilitate the detection of hidden muscle activity in surface EMG baseline recordings.

The current study also employed the MSE analysis to characterize the surface EMG baseline recordings in the nonlinear dynamic domain. Entropy is an approach to quantify the creation of information in a time series. Compared with single entropy measurement at the original time scale, the MSE analysis can help better understand the signal dynamic properties over different time scales. This was confirmed by the different MSE curves obtained from computer simulations of reference data and activity data, as well as from experimental surface EMG baseline recordings of ALS and healthy control subjects.

The results from the MSE analysis and the PSD analysis were consistent in this study. Compared with the reference data (i.e. white noise), surface EMG baseline from the activity data contains less high frequency components, and demonstrates relatively high regularity (orderliness). Therefore, a surface EMG baseline involving more hidden muscle activity (i.e. with higher SNR or activation rate) is likely to result in a lower entropy value at relatively small scale factors. However, the coarse-graining procedure is able to filter out the relatively high frequency oscillations scale by scale. It follows that for relatively large scale factors, the coarse-grained signals from the activity data are likely to be more irregular than those from the reference data.

The MSE analysis is more complicated than the PSD analysis. On the other hand, it can demonstrate advantages over the PSD analysis for detection of hidden muscle activity. Fig. 7 indicates that although the PSD analysis of single-channel EMG signals failed to show a significant difference between the healthy control and ALS data groups, the MSE analysis was able to discern such a significant difference at relatively large scales ($p < 0.05$, with scale factors larger than 8). This demonstrates that the proposed MSE analysis is more sensitive than the PSD analysis in characterizing different signal structures of surface EMG baselines in the presence or absence of hidden muscle activity. This also confirms the necessity and robustness of using the MSE patterns over different scales for hidden muscle activity detection.

For both PSD and MSE analyses, this study examined their dependence on the contribution of hidden muscle activity to surface EMG baseline through modeling different SNRs and activity rates. It was found that the yielded difference between the reference and activity data groups is well correlated with the SNR and activity rates. This suggests that the PSD and MSE analyses can be used not only to detect the presence of hidden muscle activity in surface EMG baseline, but also to quantify the relative contribution or power of such hidden activity in surface EMG baseline.

Limitation of the Study

The main limitation of the current study is that the origins of the hidden muscle activity in surface EMG baseline are not clear. Thus its clinical relevance remains somewhat ambiguous. It is likely the hidden muscle activity may be from a combination of different origins (e.g., fibrillations potentials, fasciculation potentials, complex repetitive discharges, unintentional motor unit discharges, etc.). With the current experimental setup, it is difficult

to distinguish between the different types of signals that may contribute to the hidden muscle activity. This would require an improvement of experimental design and signal analysis methods. For example, a simultaneous recording of concentric needle and surface EMG signals from resting muscles of ALS subjects may be necessary. The additional information from needle EMG processing may help to provide more definite information about the nature of the hidden muscle activity in surface EMG baseline.

In addition, pooled data analysis of ALS and healthy control subjects were performed to reveal the significant difference between their surface EMG baselines, whereas the significance at an individual subject level was not demonstrated. To promote possible use of the presented method as a diagnostic or investigatory tool, a larger study with many more control subjects and ALS patients is necessary to quantitatively assess the difference between individual subjects.

CONCLUSION

This study explored the feasibility of detecting hidden muscle activity in surface EMG baseline by PSD analysis and MSE analysis, respectively, using both computer simulations and experimental recordings. From the simulated signals it was found that although the surface EMG baseline recordings with and without hidden muscle activity yielded no distinguishable difference in the time domain, they demonstrated a significant difference in the frequency and signal complexity domains with the PSD and MSE analyses. These findings were further confirmed by applying similar analyses to electrode array surface EMG baseline recordings of a group of healthy control and ALS subjects. Compared with the PSD analysis, the MSE analysis appeared to be more sensitive for detecting the difference in surface EMG baselines between the two groups. To promote the presented analysis as a useful diagnostic or investigatory tool, future studies are necessary to assess the pathophysiological nature or origins of the hidden muscle activity, as well as the baseline difference at the individual subject level.

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Figure 1.

Three experimental fasciculation potential templates used for simulation of hidden muscle activity by scaling their amplitude and duration.

Figure 2.

An example of computer simulated signals. From top to bottom: (a) hidden muscle activity generated from 2000 origins; (b) Gaussian white noise; (c) simulated surface EMG baseline by a summation of (a) and (b) at 0 dB SNR; (d) simulated surface EMG baseline by a summation of (a) and (b) at 10 dB SNR.

Figure 3.

PSD (left panel) and MSE (right panel) results of simulated reference data and activity data with different SNRs.

Figure 4. PSD (left panel) and MSE (right panel) results of simulated reference data and activity data with different activity rates.

Figure 5.

An example of surface EMG baseline recordings from (a) a healthy control subject; and (b) an ALS subject.

Figure 6.

PSD (left panel) and MSE (right panel) results of experimental surface EMG baseline recordings from healthy control and ALS subjects (averaged from multiple channels of all the selected baseline segments). The asterisk sign “*” in the MSE curve represents significant difference in entropy value between ALS and control data groups at the specific scale factor.

Figure 7.

PSD (left panel) and MSE (right panel) results of experimental surface EMG baseline recordings from healthy control and ALS subjects, when only a single channel (off muscle innervation zones) was randomly selected from the electrode array and processed for each data segment. The asterisk sign “*” in the MSE result represents significant difference in entropy value between the two groups at the specific scale factor.

Table I

Parameter assignment for simulation of hidden muscle activity in surface EMG baseline recordings

Parameter	Distribution	Mean	SD	Range
Action potential duration	Uniform	-	-	6–24 ms
Scaling factor: a_i	Gaussian	2×10^{-4}	0.5×10^{-4}	± 2 SD
Firing rate: f	Gaussian	8 Hz	4 Hz	2–20 Hz
ISI	Gaussian	$1/f$	$20\% \times 1/f$	± 2 SD
SNR	-	-	-	10, 0, -10 dB
Activity rate	-	-	-	10%, 40%, 100%