Published in final edited form as:

IEEE Trans Neural Syst Rehabil Eng. 2018 September ; 26(9): 1878–1888. doi:10.1109/TNSRE.2018.2864317.

A Novel Interpretation of Sample Entropy in Surface Electromyographic Examination of Complex Neuromuscular Alternations in Subacute and Chronic Stroke

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Abstract

The objective of this study was to develop sample entropy (SampEn) as a novel surface electromyogram (EMG) biomarker to quantitatively examine post-stroke neuromuscular alternations. The SampEn method was performed on surface EMG interference patterns recorded from biceps brachii muscles of nine healthy control subjects, fourteen subjects with subacute stroke, and eleven subjects with chronic stroke, respectively. Measurements were collected during isometric contractions of elbow flexion at different constant force levels. By producing diagnostic decisions for individual muscles, two categories of abnormalities in some paretic muscles were discriminated in terms of abnormally increased and decreased SampEn. The efficiency of the SampEn was demonstrated by its comparable performance with a previously reported clustering index (CI) method. Mixed SampEn (or CI) patterns were observed in paretic muscles of subjects with stroke indicating complex neuromuscular changes at work as a result of a hemispheric brain lesion. Although both categories of SampEn (or CI) abnormalities were observed in both subacute and chronic stages of stroke, the underlying processes contributing to the SampEn abnormalities might vary a lot in stroke stage. The SampEn abnormalities were also found in contralateral muscles of subjects with chronic stroke indicating the necessity of applying interventions to

contralateral muscles during stroke rehabilitation. Our work not only presents a novel method for quantitative examination of neuromuscular changes, but also explains the neuropathological mechanisms of motor impairments and offers guidelines for a better design of effective rehabilitation protocols toward improved motor recovery.

Keywords

Neuromuscular changes; biomarker; sample entropy; stroke; surface electromyography

I. INTRODUCTION

STROKE is the leading cause of acquired disability in adults worldwide [1]. The interruption of the corticospinal tract after stroke is the leading cause of hemiplegia [2]. However, the effect of a hemispheric brain lesion on the survival and function of motor unit (MU) in paretic muscles remains unclear. Since a MU is regarded as the basic functional unit of the neuromuscular system, it is of great importance to identify pathological changes in the MU following stroke. Continuous efforts in this direction can explain specific mechanisms that promote functional and anatomical changes in the spastic paretic muscles. This can guide the development of effective treatments for stroke survivors.

To examine MU alternations in paretic muscles of stroke patients, both bioptic and electrophysiological studies have been conducted, and their findings are diverse and even contradictory [3], [4], [5]. In addition, these methods often involve painful procedures such as invasive detection or electrical stimulations.

Surface EMG is an alternative electrophysiological approach that enables noninvasive examination of MU behaviors. Various alterations of the MUs including their number in a single muscle and their structural/firing properties could be reflected by different morphological changes in the surface EMG signals [6], [7]. On this basis, multiple methods for analyzing surface EMG interference patterns [8], [9], [10] have been proposed across broad research programs for clinical evaluation and diagnosis of neuromuscular diseases [11]. For example, common techniques involve counting of zero-crossings [12] and firing spikes [13], measuring the mean rectified value (MRV) and the root mean square (RMS) amplitude [14]; other options include power spectral analysis [15], [16] of the surface EMG signals.

Studies of the EMG-force relation [17], [18] plays an important role in identifying changes in neural or muscular components of the MU. Recently, the clustering index (CI) was proposed by Uesugi *et al.* [19] to quantitatively evaluate the clustering degree of surface EMG signals. It can effectively discriminate neurogenic and myopathic changes. In the CI analysis, surface EMG with a flat and dense morphology is likely to have an abnormally low CI value indicating myopathic changes. In contrast, a surface EMG condensed into a few discrete action potential spikes with large amplitudes corresponds to an abnormally high CI value indicating neurogenic changes [20], [21] as a result of neuromuscular disorders or injuries.

Entropy can characterize the rate of information creation and is always used to quantify the complexity and randomness of a signal or a dynamic system that generates the signal [22]. Entropy-based measurements have been constantly updated to various versions such as approximate entropy (ApEn) [23], sample entropy (SampEn) [24], fuzzy entropy (FuzzyEn), and multi-scale entropy [22], [25] with successful applications in biomedical signal processing such as electroencephalogram (EEG) and surface EMG, etc. [22], [25], [26], [27]. For example, a novel approach of FuzzyEn called inherent FuzzyEn employs empirical mode decomposition and fuzzy membership functions to increase the reliability of complexity evaluation in realistic EEG applications [27], [28], [29].

Of these versions, SampEn is a modified version of ApEn that overcomes bias caused by self-matching, relative inconsistency, and dependence on the sample length. It also reflects the overall characteristics of the signal with a simple but effective procedure and high consistency to analyze biomedical signals. As a result, advances in SampEn in analyzing short physiological time series including surface EMG has been demonstrated in many previous studies [24], [26], [30]. In one example, SampEn was used to examine the biceps brachii muscles in patients with Parkinson's disease [31], [32]. Another study reported SampEn of EMG was able to reveal higher structural complexity in patients with medial tibial stress syndrome compared with healthy controls [33]. In these studies, the EMG complexity assessed by the SampEn analysis was mainly used to discern differences between patients with neurological disorders and healthy controls. However, such differences were reported only at the subject group level. A lack of diagnostic power at the individual subject/muscle level truly hinders applications of this technique in clinical practice.

The primary hypothesis of this study is that complex neuromuscular changes occur after stroke in the form of various alternations of MU's structure and function, which can be better revealed and differentiated by a specific approach based on SampEn analysis of the surface EMG. Thus, the primary objective of this study was to evolve the SampEn analysis of surface EMG towards a quantitative examination tool for revealing neuromuscular changes in individual muscles/subjects. The SampEn-based approach described here offers diagnostic efficiency equivalent to that of the recently developed CI method by processing data from subjects with stroke. In addition, the diagnostic yield from both methods confirmed the complex neuromuscular changes as a result of stroke. It also studies whether there are different neuromuscular changes at different stages following stroke. We hypothesized that both subacute and chronic stages of stroke would exhibit differences in neuromuscular changes. We then tested this hypothesis using the proposed SampEn-based examination tool. Our work not only presents a novel method for quantitative examination of neuromuscular changes but also explains the neuropathological mechanisms underlying motor impairments after stroke. Thus, it offers guidelines for a better design of effective strategies or protocols toward improved stroke rehabilitation.

II. METHODS

A. Subjects

Twenty-five subjects with stroke (6 females and 19 males, age: 61 ± 12 years old) and nine age-, weight-, and gender-matched healthy control subjects (3 females and 6 males, age: 67 ± 7 years old) were recruited from the inpatient department of rehabilitation medicine in the First Affiliated Hospital of Anhui Medical University (FAHAMU, Hefei, Anhui Province, China). This study was approved by the Ethic Review Committee of the hospital. All subjects with stroke were categorized into two groups according to the duration of stroke. One group consisted of 14 subjects in the subacute stage of stroke (labeled as S1-S14, 30 ± 11 days since the stroke onset; Table I). The other group consisted of 11 subjects in the chronic stage (labeled as CS1-CS11, 46 ± 27 months since the stroke onset; Table II). The stroke survivors concurrently experiencing other neuromuscular disorders (such as multiple sclerosis) or brain injury as well as those unable to fully perform voluntary contractions on both sides were excluded. In addition, nine neurologically intact subjects without any neuromuscular disorder or injury (marked as C1-C9) constituted the healthy control group. All subjects gave their informed consent before every procedure. Each subject with stroke was examined with a detailed record following the Fugl-Meyer scale before the experiment; one therapist conducted all examinations.

B. Experiments

Our home-made multi-channel surface EMG recording system is shown in Fig. 1. The same system had been successfully applied in our previous work [34]. Here, each individual EMG sensor consisted of two parallel bar-shaped electrodes with a width of 1 mm, a length of 10 mm, and a between electrode distance of 10 mm. This constituted one single differential recording channel (Fig. 1b). The recording system was built with a two-stage amplifier (AD8200, Analog Devices; OPA349, Texas Instruments) at a total gain of 60 dB and a band-pass filter at 20–500 Hz for each channel. All recorded signals were converted into digital data with a 16 bit analog-to-digital converter (ADS1198, Texas Instruments) at a sampling rate of 1 kHz per channel. The digital data were transferred and restored to the hard disk of a portable computer through a USB cable for further analysis. All recorded signals were displayed on computer's screen in real-time to monitor the quality of the data during the experiment.

The experiment was carried out in a quiet testing room to reduce the impact of the environmental noises. During the experiment, the subjects were seated comfortably in a mobile chair or wheelchair placed alongside a height-adjustable desk with their elbow of the tested arm bent at 90 degrees against the table. The data were recorded on both the paretic and contralateral sides of the subjects with stroke in a random order. For control subjects, either the dominant side or the non-dominant side was studied.

An EMG sensor was placed on the skin surface to target the biceps brachii muscle of the tested arm with its electrode bar perpendicular to the muscle fibers. A large round reference electrode (Dermatode; American Imex, Irvine, CA) was placed on arm fossa cubitalis on the same side. The subjects were asked to generate a series of isometric muscle contractions

of elbow flexion at different force levels. Mean-while, the experimenter offered a resistant force toward the inner side of the tested forearm near the wrist to facilitate muscle force generation. At the beginning, the subject was encouraged to perform three maximal voluntary contractions (MVCs). No force measurement or feedback was required in this study. Alternatively, the MVC used here was defined when the subject performed muscle contractions with maximal efforts. This condition could be determined by monitoring the EMG amplitude and identifying its maximum across the three repetitions. The determined MVC was used as reference for generation of multiple force levels. In a following single trial, the subject was instructed to perform elbow flexion with graded increasing force levels, roughly corresponding to 10%, 30%, 50%, 70%, submaximal (90%) and almost (100%) MVC. The subject subjectively determined all force levels, which were estimated roughly in terms of the MVC percentage via the EMG amplitude. This protocol has been frequently adopted in clinical practice and applied in previous studies [30], [35]. The subject performed a stable isometric muscle contraction at each force level for at least 3 s. As a result, the recorded surface EMG from the single trial exhibited graded EMG interference patterns. At least three trials were completed, and the subject performed more trials to produce a sufficient amount of data. The subject was given a sufficiently long resting period between two consecutive trials to avoid mental or muscular fatigue. The recorded raw surface EMG data were finally imported into the MATLAB (version R2015a, MathWorks, Natick, MA, USA) software for offline analysis. Fig. 2 shows a block diagram of the data analysis processes described below.

C. Data Preprocessing and Segmentation

The collected surface EMG signals were in satisfactory condition and of good quality. Thus, only a few simple methods were used to reduce noises. The recorded signal was filtered with a fourth-order zero-lag non-causal Butterworth band-pass filter set at 20–500 Hz to eliminate potential low-frequency motion artifacts and high-frequency interferences. Then, a set of second-order notch filters were used to remove the 50-Hz power line interference and its harmonics. In each trial, the graded interference EMG signal was divided into several non-overlapping epochs, each with a time length of 1 s (equivalent to 1000 sample points at the sampling rate of 1000 Hz). These epochs were deliberately selected during stable isometric muscle contractions at certain force levels. Those epochs with obvious muscle force variation were discarded. By pooling all epochs with various force levels, we finally obtained approximately 30 epochs for each tested muscle.

D. CI Analysis

CI was used to quantify the uneven distribution of the processed signal. It contains three main steps to develop the CI method as a diagnostic marker including CI calculation, establishment of a normal range, and evaluation of abnormality with respect to the normal range in terms of a Z-score [19], [36]. The main idea of using the CI method is also involved in the proposed SampEn-based approach, and thus we briefly review the CI analysis here as described in the literature [19], [20], [36].

To calculate CI, the signal was divided into a series of non-overlapping consecutive windows in a time length of 15 ms. Such a time length was recommended to ensure that a large and

individual MUAP can be covered [19]. Suppose that A_t is the unitary area value of the t -th window in an epoch with K windows. The differential sequences of area value between every consecutive windows (DA_t), between every second windows (DB_t), and between every third windows (DC_t) can be calculated. The CI was defined as

$$CI = \left\{ \sum_{t=1}^{K-1} DA_t^2 + \sum_{t=1}^{K-2} DB_t^2 + \sum_{t=1}^{K-3} DC_t^2 \right\} / \left(6 \cdot \sum_{t=1}^K A_t \right). \quad (1)$$

The CI ranges from 0 to 1, and the especially high values correspond to highly clustered surface EMG characterized by isolated large MUAPs appearing like sparse spikes [21].

The CI value was also modulated by the muscle contraction level [19]: The increase in contraction levels resulted in a lower CI value. The effect of contraction level on the CI has to be carefully modeled before this method is calibrated as a diagnostic tool. Prior users of the CI method reported an approximately linear relationship between the CI value and the EMG area (which was used to account for the contraction level) using a double logarithmic scale [19]. This was also the case for data in our study. Consequently, two values—namely a $\log(\text{area})$ and a $\log(\text{CI})$ —were derived from each analysis epoch and expressed as a data point in the CI-area plot.

The data points derived from a group of analysis epochs can be scattered to form a cloud over the CI-area plane. In order to judge abnormality via interference EMG analysis, the normal reference had to be established to calibrate the diagnostic marker expressed as the CI. In our study, the data points from the control muscles of all neurologically intact subjects as well as the contralateral muscles of all subacute stroke subjects were used to form a normal cloud. This was scattered into a favorable linear zonal region in the double logarithmic scale. To define the distribution of the normal cloud, linear regression analysis was performed on all data points of the normal cloud for both $\log(\text{CI})$ and $\log(\text{area})$. As explained above, the resulting regression line was used to model the relationship between the CI and the muscle contraction level for the normal data. Then, for each epoch/data point, the deviation defined by its upright distance between the $\log(\text{CI})$ and the linear regression line was calculated. For all analysis epochs from each tested muscle, these deviation values were pooled and averaged to obtain a mean residual (denoted as R_m). Subsequently, we calculated the mean μ_C and standard deviation σ_C of the R_m values from the control muscles of all healthy subjects and the contralateral muscles of all subjects with sub-acute stroke. These muscles were used as the normal reference in this study. On this basis, a Z-score of the R_m was defined as $(R_m - \mu_C) / \sigma_C$ for a given tested muscle. In the original CI method, a Z-score outside ± 2.5 was routinely pre-defined as abnormal. In detail, a tested muscle with a Z-score higher than $+2.5$ indicated neurogenic changes while a Z-score lower than -2.5 showed myopathic changes [21].

E. SampEn Analysis

The SampEn analysis was developed as a quantitative diagnostic indicator. To calculate SampEn from a time series $x(n)$, a series of delayed vectors in the m -dimensional and $m+1$ dimensional spaces were constructed, respectively. For a clearer description of the SampEn algorithm, the concept of match between two vectors is emphasized. A match occurs when the distance between two vectors is lower than a given threshold (the tolerance r). The distance was defined by the maximum difference of each corresponding element between both vectors. For a vector in the m -dimensional space, the probability of a “match” with all other vectors in this space (i.e. the number of match divided by the total number of vectors) was calculated. The final matching probability was obtained by averaging the probability values over all vectors in the space denoted as $B^m(r)$. Similarly, the probability $A^{m+1}(r)$ can be computed for the $m+1$ -dimensional space. The SampEn of the time series was then defined as:

$$SampEn(x, m, r) = -\ln[A^{m+1}(r)/B^m(r)]. \quad (2)$$

In the study, the SampEn was calculated for each epoch. In the SampEn calculation, we empirically set $m = 2$ and r to be 0.25 times standard deviation (SD) of the epoch to be processed. Such settings were recommended in previous studies [23], [24], [37], [38]. Similar to the CI method, it is necessary to consider the effect of the muscle contraction level. When the SampEn was plotted versus the area of the epoch, we surprisingly found that the SampEn value maintained an almost horizontal trend with slight fluctuations while the signal area was increased. This horizontal trend was especially evident for the data from the healthy controls. This was also the case for stroke subjects but with relatively larger fluctuations. Given this property, the linear regression employed in the CI method can be straightforwardly replaced by an averaging approach. On this basis, the SampEn values were averaged across all analysis epochs of each muscle to obtain a mean SampEn denoted as Em . Subsequently, these Em values from the control muscles of all healthy subjects and the contralateral muscles of all subjects with subacute stroke were pooled together as the normal reference. Their mean μ_E and standard deviation σ_E were calculated accordingly. For a given tested muscle, we defined a Z-score of Em as $(Em - \mu_E)/\sigma_E$. In the original CI method, a Z-score outside ± 2.5 was routinely pre-defined as abnormal. In detail, a tested muscle with a Z-score higher than $+2.5$ indicated neurogenic changes while a Z-score lower than -2.5 showed myopathic changes [24].

Inspired by the CI method, Z-scores within ± 2.5 are predefined to be normal with diagnostic purpose. According to the principle of SampEn, highly clustered signals tend to have a lower SampEn. Therefore, a muscle with a Z-score below -2.5 was pre-defined as experiencing primarily neurogenic changes; on the contrary, a Z-score above $+2.5$ was likely neurogenic changes. Please note that this pre-defined diagnostic criterion was reversed from that of the CI method to identify neuropathy or myopathy.

F. Statistical Analysis

There were three subject groups recruited in this study: two groups of stroke subjects had their muscles tested bilaterally (i.e., on both the paretic side and contralateral side) and muscles on either side of control subjects were tested. Therefore, all tested muscles can be categorized into five muscle groups by the subject group and side. A series of statistical analyses were designed to examine the effect of multiple variables (e.g., subject group, stroke phase, side) on diagnostic decisions expressed as Z-scores as well as to evaluate the diagnostic power of both methods in discriminating neuromuscular changes.

Four separate t-tests were applied on Z-scores between each of the four stroke muscle groups (both subacute and chronic phases combined with both paretic and contralateral sides) and the control muscle group, to primarily examine stroke-induced abnormalities. A two-way repeated-measure ANOVA was performed on Z-scores with the side (contralateral side vs. paretic side) as a within-subject factor and stroke subject group (i.e., the stage of stroke, the subacute stage vs. the chronic stage) as a between-subject factor, to simultaneously examine the effect of the side and stroke phase.

Prior to each test, an F-test was used to test variance homogeneity. All of these statistical analyses were carried out for the Z-scores derived from CI or SampEn, separately. To compare the performance of the two diagnostic methods, the results were analyzed via linear regression analysis. To verify the relationship between the SampEn of EMG and the muscle strength, one sample T-test was applied to the slopes from each muscle group; the slope of each muscle was obtained from regression analysis to the corresponding data points. The level of statistical significance was set to $p < 0.05$ for all analyses. When necessary, post-hoc pairwise multiple comparisons with a Bonferroni correction were used. All statistical analyses were completed using SPSS software (ver. 16.0, SPSS Inc. Chicago, IL).

III. RESULTS

Fig. 3 illustrates examples of the SampEn-area plots derived from four representative muscles. This is visually observed in Fig. 3—the SampEn derived from a single muscle maintains a flat trend with increased muscle contraction level represented by the larger area. When a linear regression analysis was performed on the SampEn and the corresponding area from a single muscle, the slope was almost equal to zero. More specifically, the average slope was 0.00051 for control muscles, -0.00354 for the contralateral muscles, -0.04271 for the paretic muscles of subjects with subacute stroke, -0.00274 for the contralateral muscles, and -0.03362 for the paretic muscles of subjects with chronic stroke. Furthermore, a one sample t-test indicated no statistical difference between the slope and zero ($p > 0.05$). These results confirm our previous assumption presented above that the SampEn was almost independent on the muscle contraction level. This allows an averaging approach performed on the SampEn values of the analysis epochs for each muscle, which is simplified from the regression analysis and deviation calculation involved in the routine CI analysis.

Fig. 4 showed seven 1-s analysis epochs of surface EMG signals selected from 7 muscles of four subjects in the three subject groups. These include one control muscle, both the contralateral and the paretic muscles of two subjects with subacute stroke, and one subject

with chronic stroke. Through visual appearance, these epochs have comparable area values, but their corresponding CI and SampEn values vary markedly. The variations in the CI and SampEn values could be associated with differences in the signal morphology. Specifically, the epoch with a relatively higher CI value tended to yield a lower SampEn value; the converse was equally true.

After applying the CI method to all analysis epochs, the results of the CI-area plot is illustrated in Fig. 5 for the normal cloud (including the control muscles of all healthy subjects and contralateral muscles of all subjects with subacute stroke) as well as with the paretic muscles in both the subacute stroke group and chronic stroke group. The data points from the contralateral muscles of all subjects with chronic stroke are not shown (to simplify the figure). For the normal cloud (light grey background), the CI showed a decreasing trend as the contraction level increased. This was suitable for a linear regression analysis ($y = -0.075x - 0.811$). The hollow circle represents the epochs of the paretic side of all subacute stroke subjects with a considerable part distributed above the normal cloud. The CI showed a more discrete distribution for the square from the paretic side of chronic stroke subjects.

Z scores derived from the CI method and the SampEn method are given in Fig. 6 for all tested muscles in three subject groups. Using the CI method (Fig. 6a), the resulting Z-scores derived from the control muscles (0.646 ± 0.425 , mean $\pm$ SD) and the contralateral muscles of subjects with subacute stroke (-0.485 ± 0.878) were located within the predefined normal range ± 2.5 . For the paretic muscles, 5 of 14 subjects with subacute stroke (0.986 ± 2.059) and 3 of 11 subjects with chronic stroke (1.535 ± 1.589) had Z-scores outside the normal range; these were diagnosed as abnormal. In addition, for the contralateral muscles of 11 subjects with chronic stroke (0.273 ± 2.223), four subjects had Z-scores outside the normal range as well. By comparing muscle group means, no significant difference was reported between the control muscle group and any of other four muscle groups from the subject with stroke ($p > 0.05$). The ANOVA reported no significant main effect of either the stroke stage ($F = 1.451$, $p = 0.241$) or the side ($F = 0.063$, $p = 0.804$). However, the F-test showed that *all* four muscles group from subjects with stroke had significantly larger variance of Z-scores than the control muscle group ($p < 0.05$) despite the lack of significant difference in group means. Further, the variance of paretic muscles was significantly larger than that of contralateral muscles for the subacute stroke group ($p = 0.002$), but such a variance difference was found to be insignificant for the chronic stroke group ($p = 0.533$).

The Z scores of SampEn from each muscle group were reported in Fig. 6b. Similarly, we can observe that the Z-scores of control muscles (-0.827 ± 0.555) and contralateral muscles of subjects with subacute stroke (0.591 ± 0.765) were located within the predefined normal range ± 2.5 . For the paretic muscles, 3 of 14 subjects with subacute stroke (-0.575 ± 1.620) and 3 of 11 subjects with chronic stroke (-0.252 ± 2.166) had Z-scores outside the normal range. These were diagnosed as abnormal. In addition, 1 of 11 contralateral muscles in the chronic stroke group (-1.331 ± 0.819) had Z-score outside the normal range. There were no significant differences in the group mean of the Z-scores for the control muscle group versus any of the four muscle groups from subjects with stroke ($p > 0.05$). Besides, the ANOVA reported no significant main effect of either the stroke stage ($F = 2.204$, $p = 0.151$) or the side ($F = 0.102$, $p = 0.753$). However, variance analysis showed that any of two paretic muscle

groups in both subacute and chronic stroke had significantly larger variance of the Z scores than the control muscle group or any of the two contralateral muscle groups ($p < 0.5$).

When referring to diagnostic decisions for individual muscles, Fig. 6 shows that three subjects with subacute stroke (S3, S6 and S7) concurrently had Z-scores of the CI above +2.5 and Z-scores of the SampEn below -2.5 for their paretic muscles indicating neurogenic changes in both methods. A total of five paretic muscles (S3, S6, S7, CS3 and CS10) were diagnosed as having a neurogenic abnormality by both the CI method and the SampEn method. The paretic muscle of S5 was solely diagnosed as a neurogenic abnormality using the CI method. The paretic muscle of CS6 was consistently diagnosed as a myopathic abnormality by both methods. The paretic muscle of S4 had a Z-score from the CI method above +2.5 indicating myopathic changes, while the Z-score of the SampEn method was in the normal range but very close to the boundary approximating myopathic abnormality.

For the contralateral muscles, CS3 had a diagnostic decision of neurogenic abnormality consistent with both methods, while CS5, CS9, and CS10 had such a decision solely by the CI method. The results from the two methods are somewhat consistent: The high CI values tend to give low SampEn values, and we used the Z-scores given by the two methods as two axes to form a scatter plot of the results for individual muscles as shown in Fig. 7. These data show that the all data points were distributed near $y=-x$ showing a negative correlation between the two indexes. A regression line ($y = -0.74x + 0.03$) was obtained via linear regression on the two Z-scores of all muscles; the determination coefficient R^2 was 0.782, which represents high correlation between the two indexes.

IV. DISCUSSION

A novel interpretation of the SampEn as a surface EMG biomarker in examining the complex neuromuscular changes is presented here and applied to hemisphere stroke. The primary findings of the current study include: 1) SampEn can be used as a feasible biomarker for clinical diagnosis of neuromuscular lesions, and it has similar diagnostic power as the previously developed CI method; 2) It is feasible to reveal complex neuromuscular changes, either neurogenic or myopathic, at work in the paralytic muscles following stroke with respect to healthy control muscles at the subject group level; 3) The mixed SampEn patterns can be observed in both subacute and chronic stages of stroke, but the underlying processes contributing to the SampEn abnormalities may vary markedly with stroke stage. 4) The contralateral muscles of subjects with stroke may be somehow affected by the hemispheric brain injury as well, appearing related processes in the neuromuscular system.

A. The efficiency of SampEn-based method

In this paper, SampEn was developed as a biomarker through a surface EMG examination. It successfully achieved quantitative assessment and discrimination of neuromuscular changes in the paretic muscles of stroke victims. The SampEn analysis demonstrated its diagnostic efficiency by giving a relatively consistent outcome with the previously reported CI biomarker. In a few cases, the SampEn method and the CI method produced different diagnostic decisions on the same individual muscles due to their different calculation

procedures. This suggests different sensitivities of both biomarkers to various neuromuscular processes indicating the potential to combine both biomarkers and others toward a more accurate examination approach. This can fuse their complementary information.

Next, a calculation procedure (using a tolerance locally determined by the epoch to be processed) showed that the SampEn was independent of muscle contraction force/level. This is inconsistent with previous studies reporting that the SampEn of surface EMG is somehow regulated by the muscle contraction levels/forces [26]. Such a disagreement can be attributed to different tolerance schemes in the SampEn calculation. Previous studies always adopted a fixed tolerance across a set of EMG data. Such a global/constraint tolerance scheme takes the signal amplitude information into account and allows the resulting SampEn to be correlated with the muscle contraction level.

However, in this study, we specifically employed a local tolerance scheme to adaptively select a tolerance for every signal. Thus, the resulting SampEn was mainly focused on the signal's structure characteristics other than its amplitude. By using this force-independent character of the SampEn calculation, it is straightforward to simply average SampEn values over all data points from various muscle intensities for the tested muscle without considering the force effect. In this regard, the proposed SampEn-based examination approach was further extended to consider the convenient feature of the CI method without the need for accurate force measurements. Such convenience (no force measurement and simplified calculation) can also explain why SampEn was selected from various entropy measures. Therefore, the SampEn-based method presented here involves an even more simplified and convenient protocol for manipulating the surface EMG examination of neuromuscular changes. It is especially suitable for clinical practice.

We note that the proposed SampEn biomarker as well as the previous CI biomarker is sensitive to noise contamination in the surface EMG signals to be processed. Therefore, high quality data recording with high signal-to-noise ratios are always required. In this regard, we pay particular attention to the experimental design and signal denoising preprocessing. This issue would be satisfactorily addressed considering the development of advanced sensing technologies.

B. MU alternations following stroke

Of the 25 stroke subjects, four subjects with subacute stroke and four subjects with chronic stroke had abnormal SampEn decrease and CI increase. This indicated neurogenic changes in their paretic biceps, which might be related to the MU loss and remodeling of surviving MUs. MU loss caused by trans synaptic degeneration or disuse of spinal motoneurons after hemispheric brain lesion can lead to a decrease in the number of MUs and denervation of muscle fibers [39]. This process might also occur at a very early stage of stroke and continue for 1 year [40].

To maintain the capacity for motor function, the structure and type of the surviving MU undergoes adaptive changes in which the reinnervation of the denervated muscle fibers is a typical process. This contributes to an abnormal enlargement of the surviving MUs [41]. The enlarged MUs subsequently produce abnormal MUAPs with multiple phases and greater

amplitude, finally overlying into sparse isolated and highly aggregated EMG signals. In addition, altered MU control properties may simultaneously occur in the paretic muscles. For example, the reduced MU firing rate [42], [43], [44], the compressed MU recruitment threshold [39], [45], and the increased degree of MU firing synchronization [46]—as well as the supplementary recruitment of enlarged MUs during muscle contraction—might eventually lead to an abnormally high CI and a low SampEn.

One subject with subacute stroke and one subject with chronic stroke had their surface EMG signals from paretic muscles characterized by abnormal CI decrease and SampEn increase indicating myopathic changes under the diagnostic criteria of the original CI method. This could be related to muscle fiber atrophy (i.e., wasting of muscle fibers) as the main cause of myopathic changes. Atrophy of muscle fibers, especially type II fibers, was reported in paretic muscles in stroke [3], [47]. This could also be attributed to differential loss of larger and superficial MUs in the paretic muscles [48]. These circumstances might lead to flatter and denser surface EMG signals characterized by lower CI values as well as larger SampEn values. Please note that the differential loss of MUs is truly a factor of neurogenic changes other than myopathic ones. This implies limitation for traditional distinction of both neurogenic and myopathic changes by using the CI method. Therefore, it is necessary to supplement and even revise the interpretation of CI results to draw diagnostic conclusions given these stroke findings.

We still found that the paretic muscles of most stroke victims had Z scores derived from either CI or SampEn within the normal range. However, substantial muscle weakness was reported for these muscles. This may be attributed to a deficit of descending central drive as a result of the damage of central nervous system, while the muscles in the paretic limb still function more or less normally [49]. Here, despite the reduced number of activated MUs, their recruitment and control pattern remains similar to that of healthy controls. Thus, the surface EMG signals produced by these paretic muscles are not markedly different from those by healthy control muscles except the compromised maximum of voluntary muscle contraction level. Moreover, another possible explanation for the distribution of the paretic muscle data in the “normal range” is the simultaneous occurrence of both neurogenic and myopathic processes resulting in a combined and cancelled effect without discernable abnormality [35].

C. Comparison between the subacute and chronic stage of stroke

For paretic muscles, the subacute and chronic stroke groups both showed no significant difference in group mean and variation of Z-scores derived from either the CI method or the SampEn method. This highlights their similar Z-score distribution patterns. This finding suggests that complex neuromuscular changes involving both neurogenic and myopathic processes might occur in the paralytic muscles over the long term over multiple stages because stroke onset and stroke severity vary across subjects.

The two groups of stroke subjects were categorized by the stage of stroke. They did not show any distinct difference in the diagnostic decision at the group level. The underlying factors contributing to the observed diagnostic decisions still vary significantly for the paretic muscles of individual subjects. For example, axonal or neuronal lesions can lead to

collateral reinnervation in the first month since stroke onset (equivalent to the acute or subacute stage), and spontaneous activities can be observed in the paretic muscles [41]. In terms of compensation, the number of MUAP phases and turns increase, and this is a main factor contributing to neurogenic changes. This process could diminish within a year [41]. In the chronic stage, however, collateral reinnervation occurs during the subacute phase and results in many enlarged MUs. This contributes to observed neurogenic changes in the paretic muscles. Importantly, the factor of muscle fiber atrophy occurs in the chronic stage rather than the subacute stage. The differential loss of larger and superficial MUs remains the primary factor accounting for decreased CI and increased SampEn abnormalities for subjects with subacute stroke.

D. Abnormality shown in contralateral muscles in chronic stage of stroke

Surprisingly, contralateral muscles in subjects with chronic stroke were also abnormal. They had significantly larger variations in Z-scores (derived from either CI or SampEn) than the control muscles and contralateral muscles of subjects with subacute stroke. (Both muscle groups were used to establish the normal reference). Furthermore, the contralateral muscles in chronic stroke showed no significant differences in group mean and variation from their corresponding paretic muscles. This indicates their nearly similar distribution pattern of Z-scores.

Specifically, four contralateral muscles in the chronic stage of stroke were diagnosed with Z-scores of CI larger than +2.5. Of these, one muscle simultaneously had a Z-score of SampEn lower than -2.5. These diagnostic decisions indicated neurogenic abnormality with potential processes as discussed above. The literature has shown that the unilateral lesions of the hemisphere have significant bilateral effects on the generation and control of upper limb muscles [50]. This generally explains the abnormalities found in several contralateral muscles in the chronic stage of stroke in this study. Of the four subjects with abnormalities shown in their contralateral muscles, one subject also had a paretic muscle diagnosed as being neurogenic abnormalities and another subject had a Z-score of the paretic muscle very close to neurogenic abnormality/normality boundary. The coherence of the neurogenic changes between both sides is consistent with previous findings showing that the abnormality in contralateral muscles depends on the degree of stroke severity [51]. The abnormality found in the contralateral muscles in our study suggests that the hemispheric brain lesion after stroke might lead to progressive neuromuscular changes in the muscles routinely regarded to be unimpaired—this effect is more pronounced in the chronic stage of stroke. Thus, the approach presented here is also suitable for examining impairments in contralateral muscles, and this should not be neglected in the management and rehabilitation of stroke sequelae.

E. Limitations of the current work and future expectations

The current work only focuses on the development of a surface EMG biomarker for examining stroke-induced neuromuscular changes. It should be acknowledged that at the expanses of quick and convenient implementation, the SampEn method and the CI method have limitations in discriminating specific MU properties that collectively affect the interference surface EMG signals. Although the proposed SampEn examination offers a

useful assessment of neuromuscular changes, more analytical approaches including muscle imaging and EMG decomposition at the MU level are required to provide supplementary information. A more delicate picture of MU alternations as a result of stroke can be interpreted via fusion of more information from different approaches and techniques. Our future efforts will be focused in this direction.

V. CONCLUSION

The SampEn was developed to analyze interference surface EMG signals to assess the nature of neuromuscular abnormalities. These data were classified into two categories in terms of abnormal SampEn decrease or increase, respectively. Its efficiency in discriminating neuromuscular alternations was demonstrated by yielding comparable diagnostic performance with a previously reported CI method when they were both applied to surface EMG data from subjects with stroke. Mixed SampEn (or CI) patterns were observed in paretic muscles of subjects with stroke indicating complex neuromuscular changes as a result of this brain injury. Two categories of SampEn (or CI) abnormalities were observed in both subacute and chronic stages of stroke, but the underlying processes contributing to the observed SampEn abnormalities might vary markedly in stroke stage. The SampEn abnormalities were also found in contralateral muscles of subjects with chronic stroke indicating the necessity of applying interventions to contralateral muscles during stroke rehabilitation. The SampEn method—along with its fast and simple implementation in clinical practice—can provide valuable information about post-stroke neuromuscular changes. This helps in the design of effective and individualized stroke rehabilitation protocols toward improved motor function.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under Grant 61771444, the Guangzhou Science and Technology Programme under Grant 201704030039 and the National Institutes of Health of the U.S. Department of Health and Human Services under Grant R01NS080839.

REFERENCES

- [1]. Mendis S, "Stroke disability and rehabilitation of stroke: World Health Organization perspective," *Int J Stroke*, vol. 8, no. 1, pp. 3–4, 1 2013. [PubMed: 23280261]
- [2]. Ward NS, "Mechanisms underlying recovery of motor function after stroke," (in English), *Postgraduate Medical Journal*, vol. 81, no. 958, pp. 510–514, 8 2005.
- [3]. Dattola R et al., "Muscle rearrangement in patients with hemiparesis after stroke: an electrophysiological and morphological study," *Eur Neurol*, vol. 33, no. 2, pp. 109–14, 1993. [PubMed: 8467816]
- [4]. Slager UT, Hsu JD, and Jordan C, "Histochemical and morphometric changes in muscles of stroke patients," *Clin Orthop Relat Res*, no. 199, pp. 159–68, 10 1985.
- [5]. Segura RP and Sahgal V, "Hemiplegic atrophy: electrophysiological and morphological studies," *Muscle Nerve*, vol. 4, no. 3, pp. 246–8, May-Jun 1981. [PubMed: 7242561]
- [6]. Jiang N, Parker PA, and Englehart KB, "Modeling of muscle motor unit innervation process correlation and common drive," *IEEE Trans Biomed Eng*, vol. 53, no. 8, pp. 1605–14, 8 2006. [PubMed: 16916095]
- [7]. Jiang N, Parker P, and Englehart K, "The motor unit innervation process correlation and its effects on EMG applications," in: *Conf Proc IEEE Eng Med Biol Soc*, vol. 4, pp. 4239–42, 2005. [PubMed: 17281170]

- [8]. Farina D, Fattorini L, Felici F, and Filligoi G, "Nonlinear surface EMG analysis to detect changes of motor unit conduction velocity and synchronization," *J Appl Physiol* (1985), vol. 93, no. 5, pp. 1753–63, 11 2002. [PubMed: 12381763]
- [9]. Farina D and Merletti R, "Comparison of algorithms for estimation of EMG variables during voluntary isometric contractions," *J Electromyogr Kinesiol*, vol. 10, no. 5, pp. 337–49, 10 2000. [PubMed: 11018443]
- [10]. Finsterer J, "EMG-interference pattern analysis," *J Electromyogr Kinesiol*, vol. 11, no. 4, pp. 231–46, 8 2001. [PubMed: 11532594]
- [11]. Farina D, Merletti R, and Enoka RM, "The extraction of neural strategies from the surface EMG: an update," *J Appl Physiol* (1985), vol. 117, no. 11, pp. 1215–30, 12 01 2014. [PubMed: 25277737]
- [12]. Hagg G, "Electromyographic fatigue analysis based on the number of zero crossings," *Pflugers Arch*, vol. 391, no. 1, pp. 78–80, 7 1981. [PubMed: 7279604]
- [13]. Dayan O, Spulber I, Eftekhari A, Georgiou P, Bergmann J, and McGregor A, "Applying EMG Spike and Peak Counting for a Real-Time Muscle Fatigue Monitoring System," in: 2012 IEEE Biomedical Circuits and Systems Conference (BIOCAS): Intelligent Biomedical Electronics and System for Better Life and Better Environment, pp. 41–44, 2012.
- [14]. Petrofsky JS, "Frequency and amplitude analysis of the EMG during exercise on the bicycle ergometer," *Eur J Appl Physiol Occup Physiol*, vol. 41, no. 1, pp. 1–15, 4 12 1979. [PubMed: 446467]
- [15]. Li X, Shin H, Zhou P, Niu X, Liu J, and Rymer WZ, "Power spectral analysis of surface electromyography (EMG) at matched contraction levels of the first dorsal interosseous muscle in stroke survivors," *Clinical Neurophysiology*, vol. 125, no. 5, pp. 988–994, 5 2014. [PubMed: 24268816]
- [16]. Yao B et al., "Analysis of linear electrode array EMG for assessment of hemiparetic biceps brachii muscles," *Front Hum Neurosci*, vol. 9, p. 569, 2015. [PubMed: 26557068]
- [17]. Zhou P, Suresh NL, and Rymer WZ, "Model based sensitivity analysis of EMG-force relation with respect to motor unit properties: applications to muscle paresis in stroke," *Ann Biomed Eng*, vol. 35, no. 9, pp. 1521–31, 9 2007. [PubMed: 17530407]
- [18]. Tang A and Rymer WZ, "Abnormal force-EMG relations in paretic limbs of hemiparetic human subjects," *J Neurol Neurosurg Psychiatry*, vol. 44, no. 8, pp. 690–8, 8 1981. [PubMed: 7299407]
- [19]. Uesugi H et al., "'Clustering Index method': A new technique for differentiation between neurogenic and myopathic changes using surface EMG," *Clinical Neurophysiology*, vol. 122, no. 5, pp. 1032–1041, 5 2011. [PubMed: 20869308]
- [20]. Higashihara M et al., "Evaluation of spinal and bulbar muscular atrophy by the clustering index method," *Muscle Nerve*, vol. 44, no. 4, pp. 539–46, 10 2011. [PubMed: 21826683]
- [21]. Zhang X and Zhou P, "Clustering Index Analysis of the Surface Electromyogram Poststroke," in: 2013 6th International IEEE/EMBS Conference on Neural Engineering (Ner), pp. 1586–1589, 2013.
- [22]. Zhang X, Chen X, Barkhaus PE, and Zhou P, "Multiscale entropy analysis of different spontaneous motor unit discharge patterns," *IEEE J Biomed Health Inform*, vol. 17, no. 2, pp. 470–6, 3 2013. [PubMed: 24235117]
- [23]. Pincus SM, "Approximate Entropy as a Measure of System-Complexity," in: *Proceedings of the National Academy of Sciences of the United States of America*, vol. 88, no. 6, pp. 2297–2301, 3 1991. [PubMed: 11607165]
- [24]. Richman JS and Moorman JR, "Physiological time-series analysis using approximate entropy and sample entropy," *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 278, no. 6, pp. H2039–H2049, 6 2000. [PubMed: 10843903]
- [25]. Istenic R, Kaplanis PA, Pattichis CS, and Zazula D, "Multiscale entropy-based approach to automated surface EMG classification of neuromuscular disorders," *Medical & Biological Engineering & Computing*, vol. 48, no. 8, pp. 773–781, 8 2010. [PubMed: 20490940]
- [26]. Meigal AY, Rissanen SM, Tarvainen MP, Airaksinen O, Kankaanpää M, and Karjalainen PA, "Non-linear EMG parameters for differential and early diagnostics of Parkinson's disease," *Frontiers in Neurology*, vol. 4, 2013.

- [27]. Cao Z, Lin CT, "Inherent fuzzy entropy for the improvement of EEG complexity evaluation," IEEE Trans. Fuzzy Syst, 2017.
- [28]. Cao Z, Lai KL, Lin CT, Chuang CH, Chou CC, and Wang SJ, "Exploring resting-state EEG complexity before migraine attacks," Cephalalgia, vol. 38, no. 7, pp. 1296–1306, 6 2018. [PubMed: 28958151]
- [29]. Cao ZH, Prasad M, and Lin CT, "Estimation of SSVEP-based EEG complexity using inherent fuzzy entropy," in: 2017 IEEE Int. Conf. Fuzzy Syst. (FUZZY-IEEE), Naples, Italy, Jul. 2017.
- [30]. Zhu X, Zhang X, Tang X, Gao X, and Chen X, "Re-evaluating electromyogram-force relation in healthy biceps brachii muscles using complexity measures," Entropy, vol. 19, no. 11, Nov. 2017.
- [31]. Meigal AI et al., "Novel parameters of surface EMG in patients with Parkinson's disease and healthy young and old controls," J. Electromyogr. Kinesiol, vol. 19, no. 3, pp. E206–E213, Jun. 2009. [PubMed: 18407522]
- [32]. Ruonala V, Meigal A, Rissanen SM, Airaksinen O, Kankaanpää M, and Karjalainen PA, "EMG signal morphology and kinematic parameters in essential tremor and Parkinson's disease patients," J. Electromyogr. Kinesiol, vol. 24, no. 2, pp. 300–306, Apr. 2014. [PubMed: 24462391]
- [33]. Rathleff MS, Samani A, Olesen CG, Kersting UG, and Madeleine P, "Inverse relationship between the complexity of midfoot kinematics and muscle activation in patients with medial tibial stress syndrome," J. Electromyogr. Kinesiol, vol. 21, no. 4, pp. 638–644, Aug. 2011. [PubMed: 21474335]
- [34]. Huang C, Chen X, Cao S, Qiu B and Zhang X, "An isometric muscle force estimation framework based on a high-density surface EMG array and an NMF algorithm," J. Neural Eng, vol. 14, no. 4, p. 046005, 2017. [PubMed: 28497771]
- [35]. Zhang X, Wei Z, Ren X, Gao X, Chen X, and Zhou P, "Complex Neuromuscular Changes Post-Stroke Revealed by Clustering Index Analysis of Surface Electromyogram," IEEE Trans. Neural Syst. Rehabil. Eng, vol. 25, no. 11, pp. 2105–2112, Nov. 2017. [PubMed: 28541902]
- [36]. Zhang X, Barkhaus PE, Rymer WZ, and Zhou P, "Machine learning for supporting diagnosis of amyotrophic lateral sclerosis using surface electromyogram," IEEE Trans. Neural Syst. Rehabil. Eng, vol. 22, no. 1, pp. 96–103, 1 2014. [PubMed: 23996581]
- [37]. Zhang X and Zhou P, "Sample entropy analysis of surface EMG for improved muscle activity onset detection against spurious background spikes," J. Electromyogr. Kinesiol, vol. 22, no. 6, pp. 901–7, Dec. 2012. [PubMed: 22800657]
- [38]. Zhou P and Zhang X, "A novel technique for muscle onset detection using surface EMG signals without removal of ECG artifacts," Physiol Meas, vol. 35, no. 1, pp. 45–54, Jan. 2014. [PubMed: 24345857]
- [39]. Li X, Wang YC, Suresh NL, Rymer WZ, and Zhou P, "Motor unit number reductions in paretic muscles of stroke survivors," IEEE Trans Inf Technol Biomed, vol. 15, no. 4, pp. 505–12, 7 2011. [PubMed: 21478079]
- [40]. Hara Y, Masakado Y, and Chino N, "The physiological functional loss of single thenar motor units in the stroke patients: when does it occur? Does it progress?" Clin Neurophysiol, vol. 115, no. 1, pp. 97–103, 1 2004. [PubMed: 14706475]
- [41]. Lukacs M, "Electrophysiological signs of changes in motor units after ischaemic stroke," Clin Neurophysiol, vol. 116, no. 7, pp. 1566–70, 7 2005. [PubMed: 15905127]
- [42]. Bourbonnais D and Vanden Noyen S, "Weakness in patients with hemiparesis," Am J Occup Ther, vol. 43, no. 5, pp. 313–9, 5 1989. [PubMed: 2655457]
- [43]. Hu X, Suresh AK, Rymer WZ, and Suresh NL, "Altered motor unit discharge patterns in paretic muscles of stroke survivors assessed using surface electromyography," J. Neural Eng, vol. 13, no. 4, 8 2016.
- [44]. Li X, Holobar A, Gazzoni M, Merletti R, Rymer WZ, and Zhou P, "Examination of poststroke alteration in motor unit firing behavior using high-density surface EMG decomposition," IEEE Trans. Biomed. Eng, vol. 62, no. 5, pp. 1242–1252, 5 2015. [PubMed: 25389239]
- [45]. Hu X, Suresh AK, Rymer WZ, and Suresh NL, "Assessing altered motor unit recruitment patterns in paretic muscles of stroke survivors using surface electromyography," J. Neural Eng, vol. 12, no. 6, 12 2015.

- [46]. Fujii S and Moritani T, "Spike shape analysis of surface electromyographic activity in wrist flexor and extensor muscles of the world's fastest drummer," *Neurosci Lett*, vol. 514, no. 2, pp. 185–8, 4 18 2012. [PubMed: 22414865]
- [47]. Chokroverty S, Reyes MG, Rubino FA, and Barron KD, "Hemiplegic amyotrophy. Muscle and motor point biopsy study," *Arch Neurol*, vol. 33, no. 2, pp. 104–10, 2 1976. [PubMed: 1252144]
- [48]. Lukacs M, Vecsei L, and Beniczky S, "Large motor units are selectively affected following a stroke," *Clin Neurophysiol*, vol. 119, no. 11, pp. 2555–8, 11 2008. [PubMed: 18809353]
- [49]. Fimland MS et al., "Neuromuscular performance of paretic versus non-paretic plantar flexors after stroke," *Eur J Appl Physiol*, vol. 111, no. 12, pp. 3041–9, 12 2011. [PubMed: 21455614]
- [50]. Harris ML, Polkey MI, Bath PM, and Moxham J, "Quadriceps muscle weakness following acute hemiplegic stroke," *Clin Rehabil*, vol. 15, no. 3, pp. 274–81, 6 2001. [PubMed: 11386397]
- [51]. Yarosh CA, Hoffman DS, and Strick PL, "Deficits in movements of the wrist ipsilateral to a stroke in hemiparetic subjects," *J Neurophysiol*, vol. 92, no. 6, pp. 3276–85, 12 2004. [PubMed: 15295013]

Fig. 1. Illustrations of the home-made surface EMG recording system (left), three surface EMG sensors with two electrodes for each sensor (middle), and the experimental setup (right).

Fig. 2.

Block diagram of the proposed method based on SampEn analysis. Note that the standard CI method is shown as well for comparison. Dashed boxes are processes unique to the CI method. Bold arrows represent flows to process data from normal muscles for calibrating a normal reference prior to abnormality evaluation, while non-bold arrows indicate the flows for testing a muscle.

Fig. 3.
Examples of the SampEn-area plots derived from four representative muscles.

Fig. 4. Illustration of seven representative 1-s analysis epochs of surface EMG signals. These analysis epochs are selected from a control muscle, both contralateral and paretic muscles of 2 subjects with subacute stroke and a subject with chronic stroke, respectively, during voluntary isometric muscle contractions. The signal area values of these epochs are comparable, along with their corresponding SampEn and CI values listed on the right columns of the signals.

Fig. 5.

The CI-area plot presented in double logarithmic scale for the three groups: the dominant of healthy controls and the contralateral side of subacute stroke group (light grey background), the paretic side of subacute stroke subjects (red circle), and the paretic of chronic stroke subjects (purple circle). A regression analysis (shown by the black solid line) was performed on the normal data (grey background). The normal range (dotted line) is presented within ± 2.5 of the standard error (SE) of the linear regression.

Fig. 6.

Z scores derived from the SampEn method (a) and the CI method (b) for all tested muscles in three subject groups, respectively. The Z-scores from both the contralateral muscles and paretic muscles of subjects in two stroke groups (subacute and chronic) are shown separately. The normal range (solid line) is presented within ± 2.5 of the Z-scores.

Fig. 7.

The plot of Z-scores from both the CI and SampEn methods for all tested muscles in the five subject groups.

TABLE I

PHYSICAL CHARACTERISTICS OF SUBJECTS WITH SUBACUTE STROKE

ID #	Sex	Age (years)	Duration (days)	Paretic side	Fugl-Meyer	MAS
S1	M	76	78	L	33	0
S2	M	73	63	L	15	0
S3	M	55	153	L	45	0
S4	M	80	35	L	55	0
S5	M	46	35	L	43	1
S6	M	46	34	R	37	0
S7	M	53	56	R	42	0
S8	M	58	56	L	21	0
S9	M	72	30	L	39	0
S10	F	52	40	R	25	0
S11	M	60	45	R	48	0
S12	M	61	26	L	20	0
S13	F	81	16	R	32	0
S14	M	47	40	L	27	0

M =male; F =female; L =left; R = right;

MAS = modified Ashworth scale.

TABLE II

PHYSICAL CHARACTERISTICS OF SUBJECTS WITH CHRONIC STROKE

ID #	Sex	Age (years)	Duration (months)	Paretic side	Fugl-Meyer	MAS
CS1	F	57	68	R	42	1+
CS2	M	67	33	R	40	1+
CS3	M	61	96	R	51	0
CS4	M	89	74	L	29	1+
CS5	M	76	39	R	48	1
CS6	F	60	39	L	53	0
CS7	F	58	19	L	56	1
CS8	M	59	68	L	51	0
CS9	M	50	12	R	22	1
CS10	M	47	44	L	58	0
CS11	F	53	12	R	56	0

M =male; F =female; L =left; R = right;

MAS = modified Ashworth scale.