Comparative Analysis of Surface Electromyography Features on Bilateral Upper Limbs for Stroke Evaluation: A Preliminary Study

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Abstract. The loss of upper limb functionality caused by stroke significantly influences patients daily living. Surface electromyography (sEMG) has been applied for study of stroke rehabilitation for tens of years. This paper is an attempt to evaluate stroke severity using sEMG. An experiment including four basic upper limb arm motions was carried out, with eleven able-bodied and six stroke patients being employed. Several sEMG features of bilateral upper limbs were compared for their relationship with stroke severity, and results showed that a new proposed feature named Envelope Correlation (EC) performed best. The experiment outcomes provided a prospect to evaluate stroke grade using sEMG.

Keywords: Surface electromyography (sEMG) · sEMG features
Stroke · Evaluation · Bilateral upper limbs

1 Introduction

Stroke is a medical condition in which poor blood flow to the brain results in cell death. There are about fifty million people suffering from stroke every year, and five million of them are permanently disabled [1]. Among the stroke patients, 55% to 75% survivors suffer from different levels of physical dysfunctions, more than 80% of which are on upper limbs [2]. It is reported that early assessment and cure will improve the functions of the stroke patient so as to improve their life qualities [3,4].

Nowadays, the assessments of the upper limb functions of the stroke patients are mainly divided into two types: subjective rating and objective rating. The subjective rating usually involves gauge charts and assessment done by the therapists. The common assessment includes Brunnstrom Assessment, Fugl-Meyer Assessment (FMA), Lindmark Assessment, and modified Ashworth Scale, MAS. These assessments are not able to capture the minor change of the muscles and involve subjective judgement, which varies between different therapists. Recently,

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the sEMG sensing technology has been applied to the clinic applications, which provides new ways of the upper limb recovery [5]. Elena Dalla Toffola et al. studied the myoelectric fatigue in bilateral tibialis anterior muscles of stroke patients [6]. Han [7] and Cheng [8] also did researches on stroke combining sEMG.

Feature extraction is always essential in the research of sEMG. Normally, the sEMG features can be divided into three types: time domain, frequency domain, and time-frequency domain [9,10]. Time domain features yield high recognition accuracy and cost less computational efforts. The time domain features developed by Hudgins et al. [11,12] produced good performance for representing myoelectric patterns. Alkan et al. [13] used mean absolute value (MAV) as a key input to classification system, which achieved very high classification rate. Lin et al. [14] combined MAV and AR features to build a robust gesture recognition algorithm. In comparison with time domain features, frequency domain features have much worse performance in sEMG signal classification. Instead, they enjoy better stability. In 1970, Kwatny et al. [15] applied the mean frequency of the spectrum (MNF) to detect muscle fatigue. Later, median frequency (MF) was introduced to determine changes during muscle fatigue [16]. Time-frequency domain features give a super combination between time domain features and frequency domain features. Short time fourier transform (STFT) and wavelet transform (WT) are both commonly used in this area.

In this paper, we give priority to evaluating stroke severity using sEMG sensing technique. To evaluate the relationship between sEMG features and stroke level, an experiment including four basic upper limb arm motions was carried out, with eleven able-bodied and six stroke patients being employed. Since existing sEMG features have weak relationship between stoke level. A new feature was proposed and had good performance to reflect the similarity of the bilateral upper limbs. The experiment protocol, data process, results and discussions, and the future work will be shown in the following sections.

2 Methodology

2.1 Experiment Architecture

Data Collection Device. During the experiment, a 16-channel commercial device (Delsys Trigno) was used, which is shown in Fig. 1. Delsys Trigno is a wireless, high-performing device designed to make EMG signal detection reliable and easy. The sample rate is set to 1926 Hz. According to the official document, the sEMG signals range from -5 V to 5 V, while the baseline noise is under 0.5 mV RMS. To guarantee the signal quality, the acquired data was then processed through other filters in the software. As a result, the output sEMG data was 20 Hz to 500 Hz and 50 Hz powerline noise was removed. The sEMG data was further processed by Matlab on a Windows based PC. More details of data processing are stated later in this paper.

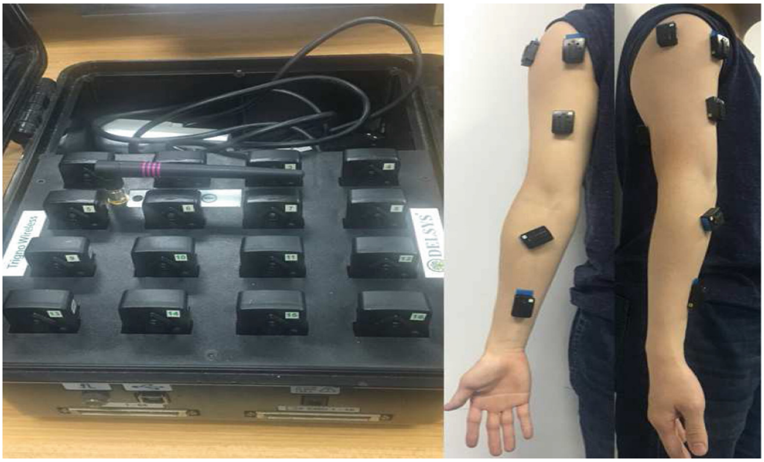


Fig. 1. Data collection device and electrode configuration.

Experiment Protocol

Electrode Configuration. The sEMG electrodes were distributed over the subjects' upper limb to mainly cover muscle groups including biceps brachii, triceps brachii, anterior deltoid, lateral deltoid, flexor carpi radialis, and pronator teres, where 6 Delsys sensors were adopted. The detection site configuration is shown in Fig. 1.

Motion Design. Four primitive upper limb motions were performed in the experiment. The four motions included lifting arm forward, elbow flexion and extension, forearm pronation and supination, and lifting arm laterally. For the second and third motions, each motion primitive comprised a pair of basic rivalry movements.

Data Collection. Over the course of the experiment, the subjects were informed to sit up straight at their comfortable position, where hemiplegic subjects were assisted by their own therapists to maintain the stable trunk posture. One single trial of a motion primitive lasted for 15 s. In each trial of the first and last motion primitive, the subjects were asked to rest for the first 5 s and execute the motion for the last 10 s, While two rivalry movements were performed and held for 5 s respectively for the second and third motion primitive. In the meantime, 10 s rest was given between adjacent trials. For healthy subjects, 8 trials were performed and recorded for each motion primitive. However, due to the heavy burden of controlling the paralysed limb, 6 trials were performed and recorded instead.

All trials were conducted by the unilateral sides of the subjects respectively. The hemiplegic subjects were asked to conduct the trials with their healthy limb first to familiarise themselves with the paradigm of motions. Motions completed by the paralysed side of hemiplegic patients were assisted by the therapists throughout the session, more specifically by keeping the posture of joints or muscles fixed. The variance of paralysis degrees of patients contributed to the failure in completing certain tasks, which was mitigated through adopting assisted or limited muscle movement with fully voluntary motion intention instead of passive ones.

Subject Information. Eleven healthy subjects participated in this experiment. All healthy subjects were between the age of 20 and 30 and had no neuromuscular disease. At the same time, 6 stroke patients were also recruited. All six stroke patients had accepted clinical examinations in an authoritative medical institution. Detailed information is given in Table 1.

Table 1. Basic information of the stroke patients.

Subject	Gender	Brunnstrom	Fugl-Meyer
1	*Male*	V-V	45/66
2	*Male*	III-IV	18/66
3	*Male*	V-VI	49/66
4	*Male*	III-II	13/66
5	*Male*	III-IV	33/66
6	*Female*	II-IV	27/66

2.2 Data Processing

Data Segmentation. In general, two methods of EMG segmentation are widely acknowledged: disjoint segmentation and overlapped segmentation [17]. In disjoint segmentation, the EMG data is separated into several parts for further feature extraction. However, in overlapped segmentation, a sliding window with certain length slides over the data. Oskoei and Hu [17] proved that overlapped segmentation performed better during EMG classification.

In our study, data processing was performed in Matlab. As stated in the experiment protocol section, a single trial of a motion primitive lasted for 15 s. For each trial, the acquired sEMG data was saved in Excel format. In order to make data analysis easier, as shown in Fig. 2, the 15-s data was divided into three periods, 5 s for each period.

Feature Extraction. Following data segmentation, feature extraction was performed. Several classic sEMG features were extracted with the window length of 5 s, which have been shown in Table 2. For all subjects, under the same motion primitive, we focused on comparing these sEMG features on bilateral upper limbs within the same period of time.

Furthermore, a new feature was constructed to evaluate the similarity of bilateral upper limbs. The feature was named Envelope Correlation (EC). EC

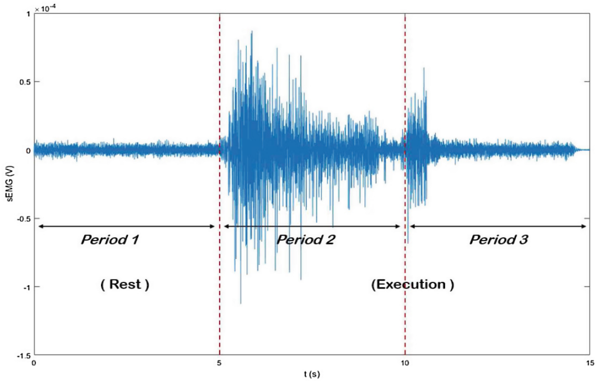


Fig. 2. Data segmentation for 15-s sEMG data.

Table 2. SEMG feature extracted in this study.

Feature extraction	Mathematical equation
Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} X_n^2}$
Waveform Length (WL)	$WL = \sum_{n=1}^{N} \lvert X_{n+1} - X_n \rvert$
Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{n=1}^{N} \lvert X_n \rvert$
Zero Crossing (ZC)	$ZC = \sum_{n=1}^{N-1}[sgn(X_n \times X_{n+1})) \cap \lvert X_n - X_{n+1} \rvert \geq threshold]\ sgn = \begin{cases} 1, if\ X \geq threshold \\ 0, \quad otherwise \end{cases}$
Median Frequency (MF)	$\int_0^{MF} P(f)df = \int_M^{\infty} P(f)df$

was built by the following steps: (a) The acquired 6-channel sEMG signals were linked into a single-channel signal. (b) Then we took root-mean-square envelopes of the single-channel data. (c) At last, we calculated the Pearson correlation coefficient of bilateral upper limbs by regarding the two set of enveloped signals as input.

3 Result

3.1 Classic sEMG Features

Table 3 shows the averaged performance of each extracted feature at the second period of the fourth motion. Two major muscle groups are mentioned in the table. Lateral deltoid is the primary muscle group for the fourth motion, while biceps brachii is the secondary muscle group. It is worth mentioning that Table 3 only shows the results of six stroke patients as the detailed results of healthy subjects shall be discussed in the future.

Table 3. SEMG Features of 4th motion at 2nd period of a trail

			stroke 1	stroke 2	stroke 3	stroke 4	stroke 5	stroke 6
MAV ($10^{-6}V$)	Lateral deltoid	healthy	66.03 ± 5.53	53.29 ± 4.5	26.05 ± 1.07	12.21 ± 0.97	24.66 ± 2.01	16.95 ± 0.85
		impaired	17.96 ± 0.44	11.88 ± 2.09	12.62 ± 1.33	1.91 ± 0.32	3.85 ± 0.78	9.87 ± 0.72
	Biceps brachii	healthy	3.04 ± 0.13	2.11 ± 0.05	2.83 ± 0.18	2.73 ± 0.22	2.67 ± 0.11	2.25 ± 0.07
		impaired	2.71 ± 0.27	12.98 ± 2.04	24.24 ± 1.41	8.73 ± 4.81	15.92 ± 2.57	7.19 ± 4.13
RMS ($10^{-6}V$)	Lateral deltoid	healthy	87.34 ± 7.35	71.72 ± 4.42	34.55 ± 1.25	16.29 ± 1.26	32.57 ± 2.7	22.51 ± 1.13
		impaired	23.48 ± 0.46	16.26 ± 3.39	16.54 ± 1.76	2.5 ± 0.43	5.07 ± 1.01	12.98 ± 0.95
	Biceps brachii	healthy	4.02 ± 0.17	2.76 ± 0.07	3.72 ± 0.24	3.58 ± 0.31	3.51 ± 0.15	2.96 ± 0.1
		impaired	3.58 ± 0.37	17.14 ± 2.69	31.89 ± 1.76	12.13 ± 6.1	21 ± 3.24	9.66 ± 5.55
ZC	Lateral deltoid	healthy	1002.33 ± 31.44	937 ± 16.87	1258.6 ± 65.65	1144 ± 42.71	1178 ± 27.81	1185.4 ± 20.48
		impaired	1033.83 ± 23.79	704.17 ± 32.43	1032.63 ± 36.65	1403.6 ± 141.84	921 ± 60.13	889.57 ± 18.44
	Biceps brachii	healthy	1822.67 ± 25.04	1657.33 ± 70.34	1514.8 ± 36.97	1317.8 ± 59.92	1615.6 ± 42.68	1759 ± 24.06
		impaired	1084.33 ± 24.79	927.5 ± 147.73	899.75 ± 44.51	1072 ± 190.73	722.6 ± 5.82	958.29 ± 56.29
WL ($10^{-6}V$)	Lateral deltoid	healthy	22.48 ± 1.63	16.91 ± 1.75	11.06 ± 0.43	4.73 ± 0.39	9.9 ± 0.7	6.8 ± 0.29
		impaired	6.3 ± 0.24	2.78 ± 0.46	4.38 ± 0.5	0.89 ± 0.06	1.18 ± 0.19	2.99 ± 0.21
	Biceps brachii	healthy	1.85 ± 0.06	1.17 ± 0.09	1.45 ± 0.07	1.2 ± 0.06	1.45 ± 0.06	1.32 ± 0.04
		impaired	1 ± 0.12	4.06 ± 0.44	7.42 ± 0.26	2.83 ± 1.42	3.91 ± 0.58	2.34 ± 1.21
MF (Hz)	Lateral deltoid	healthy	82.82 ± 0.98	74.06 ± 1.04	96.28 ± 4.61	79.25 ± 1.55	91.98 ± 1.7	92.34 ± 2.16
		impaired	77.45 ± 1.86	49.85 ± 2.88	72.6 ± 4.14	66.02 ± 5.3	52.84 ± 6.82	62.02 ± 1.44
	Biceps brachii	healthy	130.13 ± 4.78	101.47 ± 12.93	102.06 ± 1.89	60.09 ± 3.24	106.57 ± 3.04	119.69 ± 2.81
		impaired	60.15 ± 3.55	63.84 ± 8.29	69.05 ± 3.53	69.01 ± 9.56	56.79 ± 3.16	72.78 ± 2.79

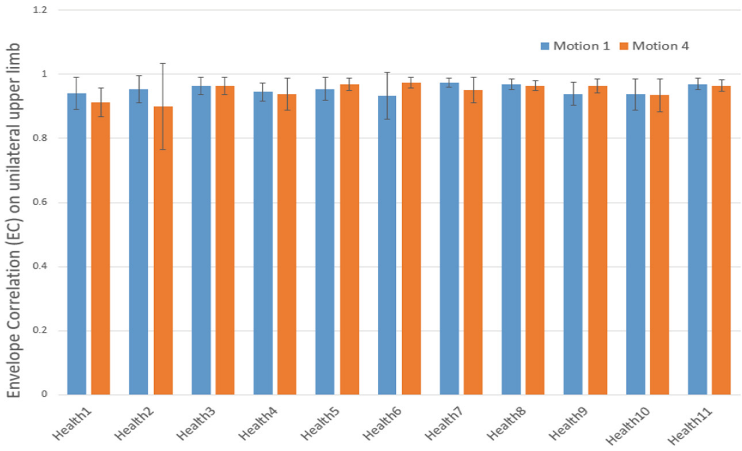
For lateral deltoid, root mean square (RMS) of the impaired side is much smaller than the other one ($p < 0.05$). On the contrary, biceps brachii performs in the opposite way. As demonstrated by other authors [18], RMS of the impaired side is significantly different from the healthy side. This conclusion is verified in our results. Besides, the distribution of RMS among six channels reflects the pattern of strength within a particular period of time. After meticulous analysis, the results show that similar strength pattern resides in all the healthy subjects as well as bilateral upper limbs. But great differences arise in the results of stroke patients. In addition, numerically, waveform length (WL) and mean absolute value (MAV) perform similarly to RMS.

Zero crossing (ZC) also shows different performances between bilateral upper limbs. For biceps brachii, the value of the healthy side is much bigger than the other one ($p < 0.05$). However, there is no consistency in comparing these two values among the six stroke patients.

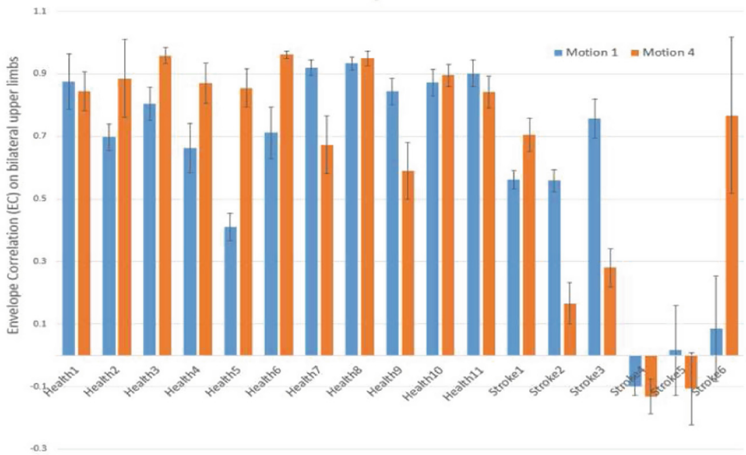
For median frequency (MF), the value of the impaired side is much lower the healthy side ($p < 0.05$) in either muscle group. Besides, the ratio of MF on the impaired side to MF on the healthy side is related to the severity of sickness.

3.2 Envelope Correlation (EC)

As shown in Fig. 3(a), EC reaches stable and high value on unilateral upper limb for each healthy subject. Under normal circumstances, for the same motion, each healthy subject behaves the same among different trials. We hope to construct a feature which may reflect the severity of sickness. So stability and high value on unilateral upper limb are just necessary conditions of a valid one.



(a) Envelope Correlation (EC) on unilateral upper limb



(b) Envelope Correlation (EC) on bilateral upper limbs

Fig. 3. Envelope Correlation (EC) on unilateral upper limb and bilateral upper limbs

Figure 3(b) shows the performance of EC on bilateral upper limbs in healthy subjects and stroke patients. For the vast majority of healthy subjects, EC reaches 0.7. More than half of the healthy score over 0.8, and some even achieve 0.9. On the contrary, EC of the six stroke patients is much lower. Overall, the first and the third stroke patient obtain high value of EC. At the same time, they indeed have had better rehabilitation effect among the six patients.

4 Discussion and Conclusion

In this study, several classic sEMG features were investigated. The results demonstrated that the mentioned classic sEMG features performed much differently between bilateral upper limbs. Besides, the general performance of these patients was: (a) lack of power in primary muscles, (b) redundant power in secondary muscles. However, the results were obtained through qualitative comparison. That is to say, we could see the differences, but we could hardly evaluate the severity of sickness numerically. Among the five features, the ratio of MF on the impaired side to MF on the healthy side might be a possible index to evaluate the severity of sickness.

A new feature, envelope correlation (EC) was also discussed. The results showed great stability in either unilateral upper limb or bilateral upper limbs of healthy subjects. And EC was proved to be a valid feature which could roughly reflect the severity of sickness. The reasons why EC could become an effective feature were as follows: (a) By connecting six channels together, EC not only contained the valuable information of all the channels, but also intuitively showed the distribution of strength among the six channels. (b) Through the root-mean-square envelopes, some of the original "impurities" of the myoelectric data were removed. The data became smooth and relatively stable.

Meanwhile, four motion primitives were involved in this study. The first and the fourth motion showed much more stable performance than the other two motions, possibly because the myoelectric signal of the second and third motions were not strong enough. Therefore, the selection of motions is another essential topic.

In further work, more motion primitives shall be added based on a larger sample to verify effectiveness of envelope correlation (EC). Besides, we will continue to explore to construct new features. Hopefully, several features will be used to establish an assessment model for medical evaluations of stroke.

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