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CRITICAL EXPONENT ANALYSIS APPLIED TO SURFACE EMG SIGNALS FOR GESTURE RECOGNITION

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Abstract

Based on recent advances in non-linear analysis, the surface electromyography (sEMG) signal has been studied from the viewpoints of self-affinity and complexity. In this study, we examine usage of critical exponent analysis (CE) method, a fractal dimension (FD) estimator, to study properties of the sEMG signal and to deploy these properties to characterize different movements for gesture recognition. SEMG signals were recorded from thirty subjects with seven hand movements and eight muscle channels. Mean values and coefficient of variations of the CE from all experiments show that there are larger variations between hand movement types but there is small variation within the same type. It also shows that the CE feature related to the self-affine property for the sEMG signal extracted from different activities is in the range of 1.855~2.754. These results have also been evaluated by analysis-of-variance (*p*-value). Results show that the CE feature is more suitable to use as a learning parameter for a classifier compared with other representative features including root mean square, median frequency and Higuchi's method. Most *p*-values of the CE feature were less than 0.0001. Thus the FD that is computed by the CE method can be applied to be used as a feature for a wide variety of sEMG applications.

Keywords: biomedical signal processing, electromyography signal, feature extraction, fractal analysis, human-machine interface, pattern classification.

1. Introduction

A surface electromyography (sEMG) signal is one of the most valuable electro-physiological signals. It is generally used to measure activities of the muscles and offers useful information for the study of numerous clinical and engineering applications [1-2]. In engineering applications, the use of the sEMG signal as an effective signal for the control of assistive devices based on gesture recognition has currently gained a high interest. This is due to the fact that the use of the sEMG signal is very easy, fast and convenient. In order to use the sEMG signal as a control signal, the feature extraction method should be used before the classification step because the raw sEMG signal contains a lot of hidden information in a huge data [2-3].

Feature extraction is a method to preserve the useful sEMG information and discard the undesirable sEMG parts [3]. Over the last two decades, a lot of techniques have been proposed and we can classify these techniques into two main types [3-8]:

– linear and non-linear analysis techniques,
– time and frequency domain techniques.

Linear analysis techniques based on time domain and frequency domain are most frequently used in sEMG recognition systems [3-5]. Features in these groups are used to describe characteristics of the sEMG signals based on an analysis of the mathematical

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functions with respect to time information and frequency information, respectively. While the well-known linear analysis techniques based on the time domain are integrated EMG (IEMG), mean absolute value (MAV), root mean square (RMS) and zero crossing (ZC), the popular linear analysis techniques based on the frequency domain are median frequency (MDF), mean frequency (MNF) and frequency ratio (FR). The IEMG, MAV, RMS and ZC features have been widely used in control of the assistive and rehabilitative devices, while the MDF, MNF and FR features are normally used in muscle fatigue determination. However, linear analysis techniques based on the time domain have been successful to some limits because this technique assumes that the sEMG signal is stationary. However, the sEMG signal is non-stationary [6]. On the other hand, linear analysis techniques based on the frequency domain have a poor performance when used as the control signal [5]. In addition, the first two technique types determine features based on linear and statistical analysis, but properties of the sEMG signal are complex, non-linear, non-periodic, and non-stationary [6-8].

Advanced techniques based on non-linear analysis gain more attention to characterize the sEMG signal. A non-linear analysis technique is essential to extract self-affinity and complexity information from the electro-physiological signals. Many non-linear analysis methods have been found in analysis of the sEMG signal, such as entropy, correlation dimension, maximum Lyapunov exponent, Lempel-Ziv complexity, Hurst exponent and fractal dimension (FD) [6-10]. However, the FD methods have shown an advance achievement in many research works compared with other non-linear analysis methods. During the past decade, the FD estimators based on the time domain have been proposed in analysis of the sEMG signal such as Higuchi's (HG) method, Katz's method, and box-counting method [9-14], whereas the FD estimators based on the frequency domain have not yet been applied.

In this research paper, we have investigated an advanced FD estimator, namely the critical exponent analysis (CE) method. This method is investigated by Nakagawa [15] as an extraction tool for identifying the electro-physiological data. Generally, the CE method has been established as an important tool for detecting the FD parameter of self-affine time-series information. It can determine the FD and Hurst exponent (H), which is calculated with respect to frequency [15], i.e. a critical exponent of the moment of power spectral density (PSD). The CE method has been successfully applied to a wide class of applications, such as identification of a speaker [16], recognition of vocal sounds [17], analysis of lung sound [18], studies of fish swimming behavior [19-20], and analysis of complex electro-physiological signals, notably the electroencephalogram (EEG) signal [21-22]. However, the CE method has never been applied for an analysis of the sEMG signal, thus the CE method may be a useful tool to characterize properties of the sEMG signal. In addition, limitations of the FD estimators based on time domain have been reported in a number of research works [10-11]. Hence, the FD estimators based on the frequency domain may provide distinguishable and valuable information. The preliminary result of this method is presented in [23].

The aim of this paper is to use the CE method to study non-linear properties of the sEMG signal and to use these properties to characterize different types of hand movements for gesture recognition and human-computer interfaces (HCIs). As a result, the FD obtained from the CE method, FD_{CE}, can be used as a feature parameter for the recognition systems. To demonstrate its classification performance, three representative features in the remainder types of the sEMG signal analysis are used for the comparative study. To the best of our knowledge no research works as yet exist which attempt to compare and evaluate four complete EMG feature types. In conclusion, four features have been evaluated and compared including:

– linear analysis technique based on time domain: RMS,
– linear analysis technique based on frequency domain: MDF,

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– non-linear analysis technique based on time domain: FD obtained from the HG method, FD_{HG},
– non-linear analysis technique based on frequency domain: FD_{CE}.

This paper is organized as follows. In Section 2, the experiments and data acquisition are introduced in detail. After that the proposed method, the CE, and three candidate methods are defined in this section with the evaluation criteria. In Section 3, comparative results of the FD_{CE}, the RMS, the MDF and the FD_{HG} features are reported and discussed. Finally, the concluding remarks are drawn in Section 4.

2. Materials and methods

In this section, experiments and data acquisition are firstly presented. Secondly, the theoretical frameworks of the CE method which is used to evaluate the FD_{CE} related to self-affine property and the representative and comparative sEMG features including RMS, MDF, and FD_{HG} are presented. Three candidate features are selected due to the popularity and effectively used in the learning parameters of a classifier. Thirdly, the evaluation criteria are proposed.

2.1. Experiments and data acquisition

Thirty healthy subjects volunteered to participate in the experiments. To determine the relationship between the sEMG features and the muscle activities, each participant was asked to perform seven types of hand movements including wrist flexion (WF), wrist extension (WE), hand close (HC), hand open (HO), forearm pronation (FP) forearm supination (FS) and rest state (RS), as depicted in Fig. 1. In addition, the sEMG signals were recorded from different electrode positions relative to muscles on the arm with varied complexity. Seven useful electrode positions on the right forearm (1-7) and an electrode position on the upper-arm (8) were selected to perform the isometric contraction activities. A common ground reference (R) was placed at the wrist. All electrode positions relative to muscles are shown in Fig. 2.

The participants were asked to maintain each movement for three seconds and each movement was repeated for four times in a trial. The order of movements was randomized in each trial. In order to measure and evaluate fluctuation of the sEMG signals, six trials were performed for each session within a day and four sessions on four separate days were acquired for each subject. Six hundred and seventy two data sets with a three-second period for each subject were conducted in total. In other words, the duration period of the data for each subject is two thousand and sixteen seconds. The results of this study are evaluated throughout a large EMG dataset that is obtained from the experiments. Hence, the investigation in this study is not dependent on the individual effects.

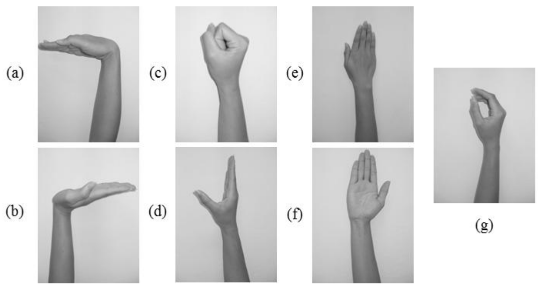

Fig. 1. Seven types of hand movements (a) WF (b) WE (c) HC (d) HO (e) FP (f) FS (g) RS.

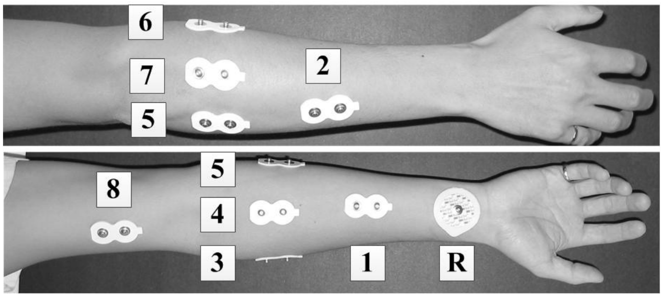

Fig. 2. Eight electrode positions (1-8) and a reference (R) on the right arm of the subject 1.

To acquire the sEMG data, the action sEMG signals were recorded by Duo-trode Ag/AgCl electrodes (Myotronics, 6140) for each electrode position. The reference electrode position (R) was acquired by an Ag/AgCl Red Dot electrode (3M, 2237). The sEMG signals were amplified by differential amplifiers (Grass Telefactor, Model 15) that were set a gain of 1000. A high-pass filter and a low-pass filter are set respectively at 1 Hz and 1000 Hz. The sEMG signals were digitized at 3000 Hz using an analog-to-digital converter board (National Instruments, PCI-6071E). More details of the experiments and data acquisition are described in [24].

2.2. Critical exponent analysis method

Fractal analysis is a mathematical tool for handling complex systems. Hence, a method of estimating FD is useful for the analysis of electro-physiological signals. The FD can yield a quantity of information embodied in the signal pattern in terms of morphology, spectrum and variance. Hence, this study has proposed the FD evaluation based on the CE method, FD_{CE}. The theoretical framework of the CE method is reviewed below.

Denote the PSD of the observed signals in the frequency domain, $P_H(v)$, and the frequency of the sEMG signal, v. If the PSD satisfies a power law, due to the self-affinity characteristic of the sEMG signal, its definition can be expressed as

$$P_H(v) \sim v^{-(2H+1)} = v^{-\beta}. \tag{1}$$

where β denotes a scaling index and H denotes the Hurst exponent related to fractal dimension FD as follows

$$FD_{CE} = 2 - H = \frac{5-\beta}{2}, \quad 0 < H < 1. \tag{2}$$

In the CE method, the α is the moment exponent and the α^{th} moment (I_α) of the PSD can be determined as

$$I_\alpha = \int P_H(v) v^\alpha dv, \quad -\infty < \alpha < \infty. \tag{3}$$

If we consider the limited frequency bands and substitute (1) into (3), the equation was given as

$$I_\alpha \sim \int_1^U v^{\alpha-\beta} dv = \frac{1}{\alpha - \beta + 1}(U^{\alpha-\beta+1} - 1), \tag{4}$$

where the upper limit of the integration U corresponds to the maximum frequency and the normalized frequency v whose lower cut-off corresponds to 1. Let $X = \alpha - \beta + 1$, thus the equation can be given as

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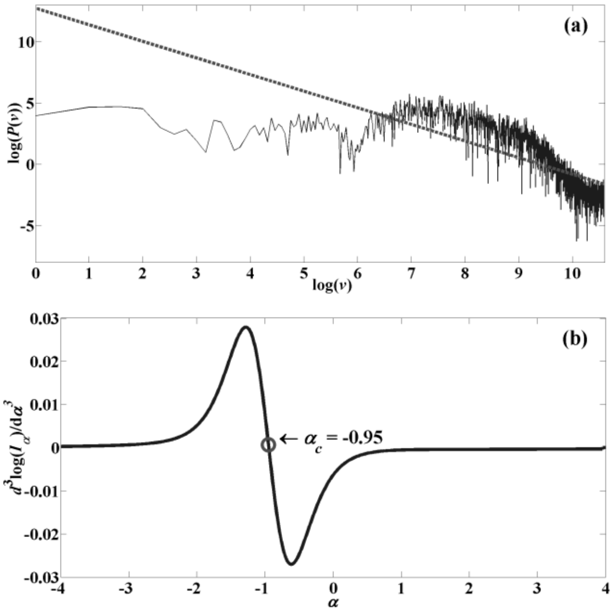

Fig. 3. (a) Log-log plot of PSD $P_H(v)$ versus frequency v - (b) Third order derivative of the logarithmic function and the zero crossing point - of the WF movement from electrode position 1 of subject 1. Note that in (a), the solid line is $P_H(v)$ and the diagonal dash line is the slope of the log-log plot of the $P_H(v)$, which is estimated by linear regression.

$$I_\alpha = \int_1^U v^{X-1} dv = \frac{1}{X}(U^X - 1), \tag{5}$$

Thus by taking the logarithm of moment I_α and differentiating it to the third order, the formula can be written as

$$\frac{d^3}{d\alpha^3}\ln I_\alpha = \frac{d^3}{dX^3}\ln I_\alpha = \frac{3U^X(U^X+1)\ln U}{(U^X-1)^3} - \frac{2}{X^3}. \tag{6}$$

Then the critical exponent (α_c) can be determined from the zero crossing point by means of the least square method or third order derivation of ln I_α (d^3ln $I_\alpha/d\alpha^3 = 0$). Finally, from the power law equation and above relation (they have been solved as detailed shown in [15]), exponent β can be expressed as

$$\beta = \alpha_c + 1 = 2H + 1 \tag{7}$$

and the estimated FD_{CE} can be calculated from

$$FD_{CE} = 2 - H = 2 - \frac{\alpha_c}{2}. \tag{8}$$

In this study, to implement the CE method according to (6), the step size of the moment exponent was set at $\alpha_\Delta = 0.01$. To show the calculating step of the CE method, the sEMG data with the WF movement from the electrode position 1 of subject 1 was presented in Fig. 3.

2.3. Comparative EMG features

RMS is a time domain feature that is related to the constant force and non-fatigue contraction. It is an agent of the linear analysis technique based on the time domain. This feature is a widely useful feature in sEMG pattern classification [2-5]. Its definition is similar to the standard deviation feature and it also gives the same information as other commonly used time domain features such as IEMG, MAV, energy, variance, simple square integral and waveform length, which can be expressed as

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}\,, \tag{9}$$

where x_n represents the sEMG signal in a segment and N denotes the length of the sEMG signal.

MDF is an agent of the linear analysis technique based on the frequency domain. It is widely used in both clinical and engineering applications [2-5]. It is defined as a frequency at which the spectrum is divided into two regions with equal amplitude; in other words, MDF is a half of the total power feature. It also gives the same information as other commonly used time domain features such as mean frequency, mean power and frequency ratio, which can be expressed as

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j\,, \tag{10}$$

where f_j is the frequency of the spectrum at frequency bin j, P_j is the sEMG power spectrum at the frequency bin j, and M is the length of the frequency bin.

HG is an agent of the non-linear analysis technique based on the time domain. It is one of the most popular fractal estimators. HG has shown a better performance than other fractal methods in the study by Esteller et al. [25] including Katz's method and Petrosian's method, and has also shown a good performance in the classification of wrist and finger movements based on sEMG signals [13-14].

Given a finite sEMG time series, $x = \{x(1), x(2), \ldots, x(N)\}$, new k sEMG time series, X_m^k, can be constructed by the following equation

$$X_m^k = \left\{ x(m), x(m+k), x(m+2k), \ldots, x\left(m + \left\lfloor \frac{N-m}{k} \right\rfloor \cdot k \right) \right\}, \tag{11}$$

where both k and m are integers, and $\lfloor \bullet \rfloor$ is the integer part of $\bullet$. The k indicates the discrete time interval between points, whereas $m = 1, 2, \ldots, k$, and m represents the initial time value.

The length of each curve, $L_m(k)$, is then calculated and defined as follows

$$L_m(k) = \frac{1}{k}\left\{ \left(\sum_{i=1}^{\left\lfloor \frac{N-m}{k} \right\rfloor} \left| x(m+ik) - x\big(m+(i-1)\cdot k\big) \right| \right) \cdot \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor \cdot k} \right\}. \tag{12}$$

Then the length of the curve for the time interval k is defined as an average of the m curves $L_m(k)$, for $m = 1, 2, \ldots, k$. As a result the linear relationship between $L(k)$ and k is plotted in the log-log graph. A relationship of this method is $L(k)\ \alpha\ k^D$. Therefore, the negative slope of the line relating $\log(L(k))$ to $\log(k)$ can give the estimate of the FD_{HG}. From the suggestion of previous work [22], we set $k_{max} = 128$.

In the experiments, sEMG data during hand movements in each activity were processed. To evaluate the sEMG feature respect to time, we set a window function as a rectangular type for all sEMG features. The window size is set to 3072 points (approximately 1 second) and the moving window with intervals is set to 1024 points (approximately 0.33 second) in this study.

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2.4. Evaluation criteria

The selection of sEMG feature extraction is an important stage to achieve optimal performance in signal pattern classification. The capability of sEMG features is validated by three properties including class separability, robustness and complexity [3-4]. In this study, we evaluate the sEMG features based on the class separability point of view. A high capability of class separability is reached when separation between movement classes is high (first condition) and variation within the movement class is low (second condition).

To evaluate the first condition, we calculated mean values of all features for each movement and each electrode position. We can observe the separation between seven types of hand movements and eight kinds of electrode positions relative to muscles in the feature space. To evaluate the second condition, a coefficient of variance (CoV) was computed. The CoV is a useful method to measure the dispersion of a probability distribution. It is similar to standard deviation (SD), the extensively used measurement of variability. The CoV is defined as the ratio of the SD to the mean value μ, which can be expressed as CoV = SD/μ. Both CoV and SD indices show how much variation or dispersion there is from the mean value. A low CoV indicates that feature values tend to be very close to the mean; whereas, a high CoV indicates that the features spread out over a large range of values. The advantage of the CoV over the SD is when the comparison of feature values with different units or largely different means. Hence, use of the CoV for comparison instead of the SD is suggested.

Box plot and analysis-of-variance (ANOVA) are used as the quantitative confirmation for the observation of the mean value and the CoV [13]. We can observe the performance of class separability from the box range in the box plot through five parameters including the sample minimum and maximum (the ends of the whiskers), the 25th and 75th percentile (the bottom and top of the box), and the median value (the band near the middle of the box). Moreover, the spacing between the different parts of the box can help to observe the degree of dispersion and skewness in the data.

On the other hand, the ANOVA is a significant statistical test to compute the *p*-value that is the one way to demonstrate the difference between features obtained from hand movements. When the *p*-value is smaller than 0.005 or 0.001, it generally means that the significant difference between their means is obtained. In this study, we compared the ability of the FD_{CE} feature with other popular features (the RMS, the MDF and the FD_{HG}) by using the above introduced evaluation indices.

Furthermore, the general use of a single feature as a learning parameter for a classifier is not powerful enough to reach the best performance in classification. For a more powerful feature vector (multiple learning parameters), the FD_{CE} should be combined with other EMG features; therefore, the relationship between the FD_{CE} feature and other representative features should be investigated. The linear correlation between FD_{CE} and each feature was calculated. If a high correlation coefficient is found, it means that the combination between the FD_{CE} and that feature do not add a great deal to the classification already achieved; whereas, if a low correlation coefficient is found, the improvement of classification performance would add more value.

3. Results and discussion

3.1. EMG raw data

Examples of sEMG signals acquired from seven forearm and one upper-arm muscle are shown in Fig. 4 according to seven hand movements, including WF, RS, FP, HO, HC, WE and FS, from left to right. From this figure we can observe that the order of movements was randomized for each trial. It is possible that the adjacent movement was the same action, as can be observed in HC movement in Fig. 4. Each row refers to sEMG signals acquired from electrode positions 1 to 8, respectively. The figure shows that the amplitudes of the sEMG signals were significantly different according to the directions of movements and also were significantly different in accordance with the electrode positions relative to muscles.

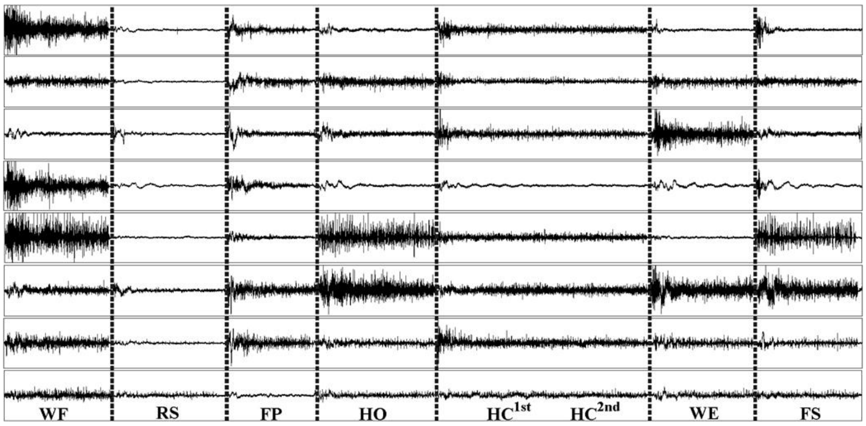

Fig. 4. Graphical representation of the eight-channel sEMG signals according to the seven hand movements.

Table 1. Mean values of the FD estimated from CE method and their CoVs from 30 subjects for 7 hand movements and 8 electrode positions.

	Movements						
Electrode positions	**WF**	**WE**	**HC**	**HO**	**FP**	**FS**	**RS**
1	2.223 (0.035)	2.312 (0.039)	2.321 (0.038)	2.200 (0.037)	2.166 (0.045)	2.190 (0.041)	2.171 (0.035)
2	2.381 (0.039)	2.311 (0.037)	2.301 (0.041)	2.434 (0.039)	2.238 (0.049)	2.299 (0.049)	2.226 (0.040)
3	2.295 (0.039)	2.315 (0.040)	2.201 (0.038)	2.432 (0.039)	2.212 (0.041)	2.245 (0.046)	2.205 (0.034)
4	2.174 (0.036)	2.184 (0.036)	2.287 (0.040)	2.199 (0.040)	2.136 (0.044)	2.182 (0.042)	2.140 (0.033)
5	2.301 (0.036)	2.284 (0.036)	2.341 (0.038)	2.213 (0.039)	2.232 (0.047)	2.173 (0.040)	2.162 (0.036)
6	2.416 (0.038)	2.305 (0.038)	2.286 (0.041)	2.492 (0.038)	2.292 (0.046)	2.327 (0.048)	2.250 (0.041)
7	2.296 (0.035)	2.372 (0.036)	2.291 (0.037)	2.338 (0.039)	2.235 (0.041)	2.258 (0.043)	2.200 (0.035)
8	2.236 (0.046)	2.233 (0.046)	2.246 (0.051)	2.206 (0.048)	2.296 (0.054)	2.149 (0.041)	2.228 (0.043)

3.2. FD based on the CE method

A large sEMG data (30 subjects on 4 separate days) that covers a wide variety of activities, muscles and fluctuation of the sEMG signals have been used for evaluating the performance of the proposed methods. Mean values of the FD_{CE} feature and their CoVs for each movement and each electrode position from thirty subjects are shown in Table 1. From the values of the respective FD_{CE} that are summarized in Table 1, we found that the FD_{CE} related to the self-affine property for the sEMG signals. Since each subject will present different sEMG patterns during hand movements.

The FD_{CE} values range between 1.855~2.754. The estimation range of the FD_{CE} is a broad band. We realize that a minute difference in a value of the FD, even at 0.1, is regarded as a

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significant change [10-22]. This contributed to the usefulness of the FD feature obtained from the CE method. Moreover, a higher FD_{CE} in the sEMG signal indicates a more complicated structure of the sEMG signals or the quantity of information embodied in a pattern.

3.3. Comparison of FD_{CE} with other features

Mean values of three candidate features (the RMS, the MDF and the FD_{HG}) and their CoVs for each movement and each electrode position from thirty subjects are respectively shown in Table 2 through Table 4. From the observation of mean values of all features in Table 1 through Table 4, it showed that all features contain more separation that is useful in separating the different movements. However, the CoVs that is used to indicate the variation of feature -

Table 2. Mean values of the RMS and their CoVs from 30 subjects for 7 hand movements and 8 electrode positions.

Electrode positions	Movements						
	WF	WE	HC	HO	FP	FS	RS
1	0.038 (0.746)	0.050 (0.555)	0.065 (0.601)	0.040 (0.802)	0.052 (0.876)	0.053 (0.806)	0.034 (0.820)
2	0.049 (0.464)	0.036 (0.587)	0.043 (0.605)	0.076 (0.383)	0.048 (0.773)	0.054 (0.608)	0.027 (0.799)
3	0.035 (0.557)	0.036 (0.512)	0.031 (0.807)	0.075 (0.389)	0.037 (0.802)	0.039 (0.686)	0.024 (0.767)
4	0.035 (0.772)	0.034 (0.715)	0.062 (0.661)	0.041 (0.743)	0.047 (0.891)	0.050 (0.784)	0.030 (0.788)
5	0.045 (0.582)	0.043 (0.601)	0.072 (0.582)	0.037 (0.755)	0.051 (0.722)	0.046 (0.841)	0.030 (0.840)
6	0.068 (0.429)	0.044 (0.647)	0.048 (0.659)	0.127 (0.326)	0.063 (0.695)	0.065 (0.595)	0.036 (0.817)
7	0.034 (0.586)	0.054 (0.499)	0.041 (0.596)	0.045 (0.492)	0.041 (0.755)	0.041 (0.676)	0.024 (0.756)
8	0.032 (0.426)	0.031 (0.403)	0.040 (0.485)	0.034 (0.505)	0.047 (0.442)	0.033 (0.655)	0.029 (0.413)

Table 3. Mean values of the MDF and their CoVs from 30 subjects for 7 hand movements and 8 electrode positions.

Electrode positions	Movements						
	WF	WE	HC	HO	FP	FS	RS
1	61.2 (0.735)	76.3 (0.528)	118.0 (0.558)	55.2 (0.868)	41.6 (0.949)	52.4 (0.877)	40.0 (0.956)
2	106.5 (0.353)	79.8 (0.516)	86.8 (0.582)	135.1 (0.284)	57.2 (0.771)	80.2 (0.649)	52.2 (0.913)
3	67.1 (0.496)	72.9 (0.487)	47.0 (0.786)	126.7 (0.298)	48.8 (0.756)	49.9 (0.661)	35.0 (0.803)
4	33.9 (0.714)	36.4 (0.746)	91.2 (0.638)	45.5 (0.771)	26.6 (0.867)	45.3 (0.847)	19.8 (0.838)
5	93.4 (0.556)	72.5 (0.585)	130.4 (0.505)	53.1 (0.820)	61.6 (0.738)	45.1 (1.007)	32.6 (1.128)
6	111.7 (0.292)	77.7 (0.537)	76.5 (0.599)	157.2 (0.201)	75.4 (0.586)	87.3 (0.520)	58.6 (0.806)
7	90.4 (0.523)	99.7 (0.354)	98.5 (0.591)	115.0 (0.456)	68.3 (0.767)	79.4 (0.704)	47.1 (0.957)
8	34.0 (0.404)	33.2 (0.410)	36.0 (0.448)	30.0 (0.475)	44.5 (0.448)	22.6 (0.592)	32.1 (0.415)

Table 4. Mean values of the FD estimated from HG method and their CoVs from 30 subjects for 7 hand movements and 8 electrode positions.

Electrode positions	Movements						
	WF	WE	HC	HO	FP	FS	RS
1	1.812 (0.055)	1.854 (0.042)	1.881 (0.043)	1.793 (0.064)	1.753 (0.082)	1.780 (0.071)	1.765 (0.065)
2	1.898 (0.030)	1.866 (0.037)	1.863 (0.045)	1.929 (0.023)	1.814 (0.065)	1.854 (0.054)	1.812 (0.055)
3	1.838 (0.045)	1.855 (0.041)	1.783 (0.064)	1.922 (0.026)	1.787 (0.068)	1.806 (0.061)	1.794 (0.055)
4	1.747 (0.065)	1.766 (0.063)	1.848 (0.052)	1.775 (0.066)	1.705 (0.086)	1.763 (0.075)	1.723 (0.067)
5	1.865 (0.043)	1.852 (0.042)	1.893 (0.039)	1.801 (0.061)	1.797 (0.069)	1.757 (0.072)	1.752 (0.066)
6	1.907 (0.025)	1.859 (0.039)	1.846 (0.046)	1.950 (0.016)	1.848 (0.050)	1.865 (0.046)	1.822 (0.050)
7	1.867 (0.041)	1.889 (0.029)	1.863 (0.046)	1.898 (0.039)	1.824 (0.060)	1.839 (0.058)	1.803 (0.056)
8	1.766 (0.043)	1.766 (0.044)	1.761 (0.048)	1.747 (0.051)	1.790 (0.044)	1.721 (0.062)	1.769 (0.040)

Table 5. Average *p*-values of 30 subjects from all hand movements for 8 electrode positions.

Features	Electrode positions							
	1	2	3	4	5	6	7	8
RMS	0.02460	0.00909	0.00024	0.06438	0.03206	0.00016	0.02252	0.06755
MDF	0.01081	0.00000	0.00000	0.00009	0.00000	0.02203	0.00000	0.04951
FD_{HG}	0.00172	0.00125	0.00001	0.00745	0.00994	0.00000	0.00615	0.15787
FD_{CE}	0.00118	0.00000	0.00000	0.00047	0.00219	0.00000	0.00003	0.03786

Table 6. The number of subjects that has the average *p*-value more than 0.001 from 30 subjects.

Features	Electrode positions							
	1	2	3	4	5	6	7	8
RMS	7	3	1	10	9	2	5	14
MDF	1	0	0	0	0	1	0	10
FD_{HG}	3	2	0	6	3	0	3	16
FD_{CE}	1	0	0	3	1	0	0	8

within a group are very high for two linear analysis techniques, RMS and MDF features. Their CoVs have a higher value than the CoVs of non-linear analysis techniques, FD_{CE} and FD_{HG} features approximately ten times, as can be observed between Table 1 and 4, and Table 2 and 3, while the variation within a group (same movement and same muscle) should be as low as possible. The reason for the relatively high variation within the group of linear analysis features is that these methods assume in the calculating procedure that the sEMG signal is a stationary signal. In our experiments, the sEMG signals contain more fluctuations (96 times per movement and per day with 4 separate days for each subject) that have definitely occurred in real-world situations; for instance, long-time use of the sEMG gesture recognition. Hence, the linear analysis techniques, RMS and MDF features have been successful to some limits. Hence, the performance of the two non-linear analysis techniques, FD_{CE} and FD_{HG}, shall be discussed. In addition, to be easily observed, the case of all features from seven hand movements of electrode position 1 of subject 27 is presented in Fig. 5 with a box plot.

The *p*-values conducted from ANOVA were used as the quantitative confirmation for the observation of the mean value and box plot. It can be used to determine the significance of the separation of feature to identify different hand movements. From Table 5, it is observed that

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the FD_{CE} and MDF features are more significant than the other features. However, from the box plot of the MDF feature, the small *p*-values are obtained from the large difference in a few movements. In other words, there is a large overlap between the box of the WF, HO, FP, and RS movements and there is a significant overlap between the box of the WE and FS movements. The high overlapping explains why the MDF feature is not a good candidate feature in sEMG signal classification. The *p*-values of the FD_{CE} for four electrode positions were less than 0.0001 while that of the FD_{HG} and the RMS were definitely higher than the *p*-values of the FD_{CE}. In addition, it has been found that the FD_{CE} has a direct relation to the electrode position. From the results, the electrode positions 2, 3, 6 and 7 are suitable for classifying hand movements.

Since each subject will present different sEMG patterns during hand movements, therefore the significance of the *p*-value should be observed for each subject. In this study, we show the number of the subject who has the average *p*-value higher than 0.001, as shown in Table 6. It shows that the FD_{HG} feature has no significance for at least two subjects for six electrode positions. On the other hand, the FD_{CE} feature has no significance (at the 0.001 level) only in five cases from the electrode positions 1, 4 and 5, but they have the significance at 0.01 statistically significant levels. From all results, it clearly demonstrates that the FD_{CE} is a more reliable feature for classifying hand movements than other candidate features. In addition, the *p*-value of electrode position 8 indicates that using this muscle in hand movement recognition is not recommended. This is due to a very low-level contraction of this muscle that is placed on the upper-arm, while the movements are performed on the hand and the wrist.

3.4. Correlation between FD_{CE} and other features

The correlations between the FD_{CE} and other candidate features were examined in Table 7. The relationships between the FD_{CE} and the MDF were highly correlated ($p < 0.0001$) because their calculation are based on the frequency domain and the relationships between the FD_{CE} and the FD_{HG} were also highly correlated ($p < 0.0001$) because their calculations are based on a non-linear analysis technique. Due to the high correlation coefficients between the FD_{CE} and the MDF and between the FD_{CE} and the FD_{HG}, the combinations of features in this group do not add a great deal to yield better classification performance. Hence, only one feature should be selected as a candidate from this group. From the experiment it is clearly shown that the FD_{CE} is definitely better than the MDF and the FD_{HG}. On the contrary, the relationship between the FD_{CE} and the RMS were not highly correlated; thus a feature vector which combines the FD_{CE} and the RMS shall yield an improvement in sEMG classification. There are a number of successful linear analysis techniques based on the time domain such as IEMG, ZC, waveform length [5, 26] and Willison amplitude [27]. The combination of features from these groups (linear analysis techniques based on the time domain and non-linear analysis techniques based on the frequency domain) would be of value in future work of sEMG signal classification.

Table 7. Correlation between the FD_{CE} feature and other candidate features including RMS, MDF and FD_{HG}. The correlation between FD_{CE} and RMS, FD_{CE} and MDF, and FD_{CE} and FD_{HG} are significant at *p*-values less than 0.05, 0.0001 and 0.0001, respectively.

Features	**Electrode positions**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
RMS	0.48	0.38	0.38	0.50	0.51	0.44	0.43	0.51
MDF	0.82	0.92	0.90	0.85	0.88	0.92	0.85	0.83
FD_{HG}	0.85	0.86	0.86	0.93	0.89	0.85	0.84	0.81

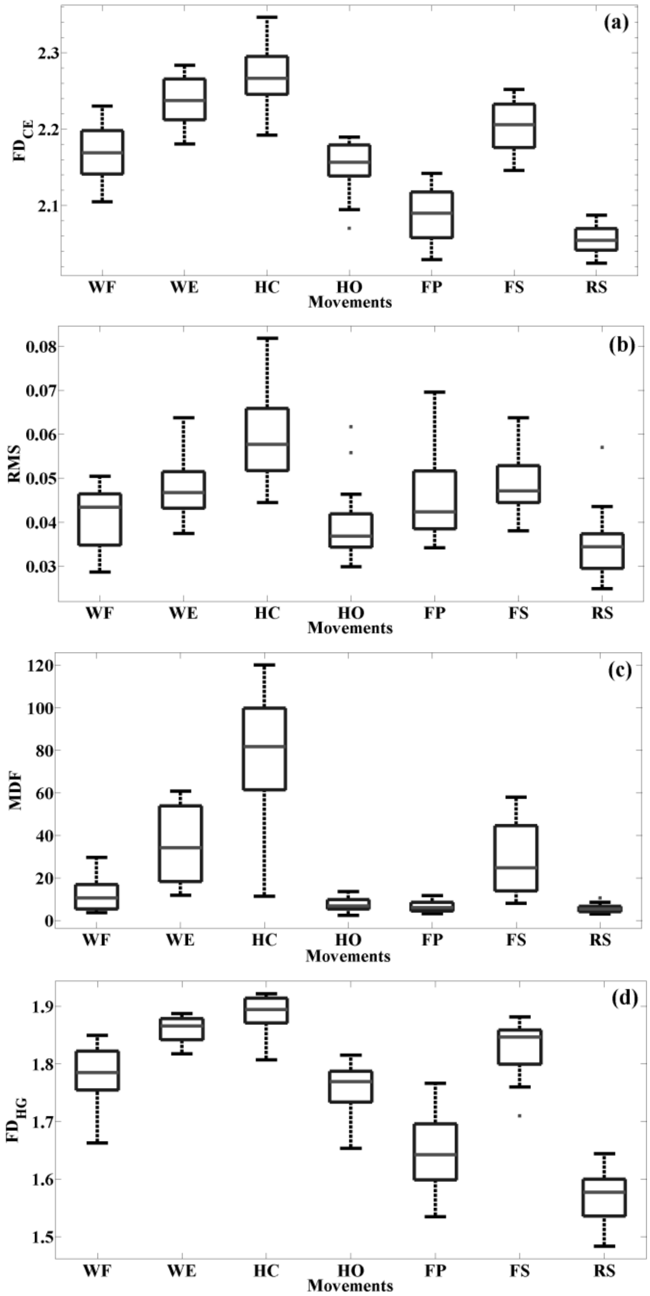

Fig. 5. Box plot of (a) FD_{CE} (b) RMS (c) MDF (d) FD_{HG} from 7 hand movements of the subject 27 and electrode position 1.

4. Conclusion

Fractal analysis of the sEMG signal from different hand movements has been proposed. We determined FD based on the CE with the time-dependence (sliding-window) method. The critical exponent value characterizes the self-affine property of the sEMG signal. The method described in this study can be considerably utilized the sEMG-based classifications and it shows a better ability than other popular sEMG features including the RMS (linear analysis technique based on time domain), the MDF (linear analysis technique based on frequency domain) and the FD_{HG} (non-linear analysis technique based on time domain). In future work, the use of FD estimated by the CE method as a learning parameter for a classifier should be evaluated. There are some successful classifiers such as linear discriminant analysis and

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support vector machine. Moreover, the optimal parameters of the CE method should be evaluated such as window length, increment step of exponent α.

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