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Feature extraction of the first difference of EMG time series for EMG pattern recognition

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ABSTRACT

This paper demonstrates the utility of a differencing technique to transform surface EMG signals measured during both static and dynamic contractions such that they become more stationary. The technique was evaluated by three stationarity tests consisting of the variation of two statistical properties, i.e., mean and standard deviation, and the reverse arrangements test. As a result of the proposed technique, the first difference of EMG time series became more stationary compared to the original measured signal. Based on this finding, the performance of time-domain features extracted from raw and transformed EMG was investigated via an EMG classification problem (i.e., eight dynamic motions and four EMG channels) on data from 18 subjects. The results show that the classification accuracies of all features extracted from the transformed signals were higher than features extracted from the original signals for six different classifiers including quadratic discriminant analysis. On average, the proposed differencing technique improved classification accuracies by 2–8%.

1. Introduction

Traditional surface electromyography (EMG) pattern recognition methods for muscle–computer interfaces have been developed under the assumption that surface EMG signals are stationary, or exhibit "stationarity" [1,2]. The term "stationarity" means that statistical properties of the signal do not change over time [3]. Generally, a weaker form of stationarity is used for the analysis of surface EMG signals based on second-order stationarity [1,2], such that signal mean and variance do not depend greatly on time differences. A signal with these characteristics can be considered weak- or wide-sense stationary.

Two approaches have been proposed for EMG pattern recognition systems, using the assumption of stationarity. Measured EMG signals could be considered stationary if (1) a whole short-time static or dynamic contraction is classified to be a single output [4–7], and (2) the static portions of a medium- or long-duration dynamic motion are classified as

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single outputs over a sufficiently short-time window [8–11]. However, limiting a motion recognition system to utilize either a short transient or a steady-state EMG signal would limit the benefits of the system. In other words, a recognition system which combines both transient and steady-state EMG signals together would increase the utility of the system for clinical applications [12,13].

In activities of daily living, a dynamic contraction is more common than a static contraction. Each activity usually contains both transient and steady-state EMG components. If both are considered as one motion with continuous classified outputs, the assumption of stationarity does not hold [14] because statistical properties of the signal consisting of mean, variance and/or spectral characteristics, continuously change over time [3]. EMG pattern recognition systems that are built only on the assumption of stationarity would fail to classify the EMG pattern in dynamic portions, particularly at the beginning and the end of the contractions [15,16].

In modern EMG pattern recognition, time–frequency and time-scale analysis methods such as short-time Fourier transform, discrete and continuous wavelet transforms [6,11,14] have been used to study time-varying properties of non-stationary EMG signals. A wavelet transform approach with a support vector machine (SVM) classifier provides better classification accuracy compared to several state-of-the-art classifiers such as the artificial neural network (ANN) and the linear discriminant analysis (LDA) [17]. However, this combination has some disadvantages in practical applications such as performance-dependence on the optimization of training, i.e., static and dynamic training, and both steps of the technique must be optimized concurrently such that required training time becomes very lengthy [16]. Moreover, classification performance of an SVM degrades over time by 14.6% when not being recurrently trained [18]. On the other hand, a combination of simple approaches using time domain (TD) analysis methods and LDA classifiers provides performance comparable to more complex classification methods including the wavelet transform, the SVM, and ANN [19,20]. The classification performance of a combined TD/LDA approach is less sensitive to changes in training sets and does not require any optimization [16,19]. Moreover, the classification performance of an LDA has been shown to degrade by only 3.6% when not being trained recurrently [18].

In general, TD methods are not designed to reliably quantify a non-stationary signal. TD features extracted from both static and dynamic portions have increased variance [21,22] and thereby degrade the performance of classifiers [15,16]. Therefore, in order to use TD methods to analyze actions associated with EMG signals, it is first necessary to understand stationarity of the measured EMG signals, and potentially render the measured EMG signals more stationary as needed [23]. However, previous studies investigating stationarity of surface EMG signals [1–3,23] reported that stationarity of the signals depends on many conditions such as the analysis window size, the type of motions and muscle contractions, and features used to characterize the signals.

From a statistical viewpoint, simple transformations such as polynomial trend removal or differencing [24] could render a measured signal more stationary and more compatible with TD methods. The differencing technique has previously been applied as a part of some TD methods in the analysis of surface EMG signals [17,21,25–28]. These features are generally computed based on statistics of the first-order difference of EMG time series, $d^{(1)}(t)$, instead of the original EMG time series, $x(t)$, and previous studies also demonstrated better classification performance of $d^{(1)}(t)$ features over $x(t)$ features. The literature review on existing EMG features extracted from $d^{(1)}(t)$ is presented in detail in Section 2. While these existing EMG derivative features have shown very high performance in the classification of upper-limb motions associated with surface EMG signals, previous studies have lacked consistency in the application of differencing, and many of them could not explain why features extracted from $d^{(1)}(t)$ yield higher accuracy compared to features extracted from $x(t)$. The question then arises whether it is the stationarity of the signals that is affected through differencing, leading to better classification performance.

Therefore, the first purpose of this study was to examine the stationarity of EMG time series with and without a differencing technique applied. The second purpose of this study was to evaluate classification performance of features extracted from $d^{(1)}(t)$ and $x(t)$ using various classifiers and analysis segment lengths of the same EMG data. The third purpose of this study was to explore new potential features of $d^{(1)}(t)$ by using existing methods applied to $x(t)$ on $d^{(1)}(t)$. Based on results from previous studies, it was hypothesized that (1) $d^{(1)}(t)$ is more stationary compared with $x(t)$, and (2) EMG features extracted from $d^{(1)}(t)$ provide better classification accuracy compared to features extracted from $x(t)$.

2. Literature review on EMG derivative feature extraction

One of the most widely used and successful features using the differencing technique is waveform length (WL). It is defined as a summation of the absolute value of $d^{(1)}(t)$ and can be considered as an extended version of integrated EMG (IEMG), which is a summation of the absolute value of $x(t)$. Oskoei and Hu [17] reports that WL yields the best performance in classification accuracy, stability, and computation load, among single TD and frequency domain features including IEMG, using three different classifiers: the SVM, ANN, and LDA. This finding has been confirmed in previous studies based on the LDA classifier [26] as well as a statistical separability measure [21].

Mean absolute value (MAV) and root mean square (RMS) are two popular features which are often used as an estimate of EMG amplitude [29]. Both features have been modified using the differencing technique in several previous studies [25–27], which are called the difference absolute mean value (DAMV) and difference absolute standard deviation value (DASDV) respectively. Kim et al. [25] and Yu et al. [27] examined the classification performance between MAV and DAMV as well as RMS and DASDV using an LDA, a quadratic discriminant analysis (QDA), a k-nearest neighbor (kNN), and a maximum likelihood estimation classifier. The classification accuracies obtained from the DAMV and the DASDV were significantly higher than the accuracies obtained from the MAV and the RMS ($p < 0.05$).

A number of TD features have been proposed to measure frequency domain contents of surface EMG signals. For example, Willison amplitude (WAMP) effectively counts the frequency of motor unit action potentials (MUAPs) firing, which can be considered as an extension of the myopulse percentage rate (MYOP) using the differencing technique. In addition, Khushaba et al. [28] proposes a new TD feature set based on the Hjorth's approach [30], which provides the spectral moments of the signal via time-differentiation. The five features proposed are based on the zero, second, and forth order moments (M0, M2, and M4), and provide very accurate classification rates (approximately 90%) for eight motions across five different upper limb positions. The M2 feature of $x(t)$ can be considered equivalent to the M0 feature, or simple square integral (SSI), of $d^{(1)}(t)$.

3. Materials and methods

3.1. EMG signal measurement

The EMG data, used to evaluate the proposed methods, were recorded from four forearm muscles in 18 (9 male, 9 female) normal subjects aged between 20 and 23 years old, as they performed eight hand, wrist and forearm motions [31]. The eight motions consisted of forearm pronation (FP), forearm supination (FS), wrist extension (WE), wrist flexion (WF), wrist radial deviation (WRD), wrist ulnar deviation (WUD), hand open (HO), and hand close (HC). All subjects are dexterous with their right hands and the shoulder was positioned at 0 degree (neutral) with an elbow in full extension.

The subjects were asked to perform 15 sessions per day for 4 separate days (60 sessions in total). Within each session, the subject performed each motion for 2 s in duration and separated each motion by a 2-s period in the rest state to avoid any transitional stage (i.e., during motion changes). The order of motions was randomized in each session. In total, 60 datasets or a total duration of 120 s per motion were collected for each subject.

EMG data were collected from four muscles consisting of: extensor carpi radialis longus (ECRL), extensor carpi ulnaris (ECU), extensor digitorum communis (EDC), and flexor carpi radialis (FCR) on the right arm using bipolar Ag/AgCl electrodes (H124SG, Kendal ARBO) with a 24-mm diameter and a 20-mm inter-electrode distance. All EMG signals were amplified with a gain of 19.5× and sampled at 1024 Hz with a 24-bit resolution by a commercial wireless EMG measurement system (Mobi6-6b, TMS International B.V.). In order to remove noise and unwanted signals, the EMG data were passed through a band-pass filter with a cutoff frequency of 20 and 500 Hz and a notch filter with a cutoff frequency of 50 Hz [32].

3.2. EMG stationarity tests

According to theory [24], a transformed time series $d^{(1)}(t)$ will be stationary for a broad class of nonstationary time series $x(t)$. Thus, it is possible that a differencing technique will allow the application of conventional EMG feature extraction methods, developed for stationary time series, to non-stationary time series.

The first difference of a time series x in discrete time t is defined as the differences between consecutive values of x, which can be described by the following expression: $d^{(1)}(t) = x(t+1) - x(t)$, where $t = 1, 2, \ldots, N-1$, and N is the total number of data points in the analyzed segment. It should be noted that the proposed technique reduces the signal length to be $N-1$.

The EMG time series were analyzed with 250-ms adjacent segments ($N = 256$ data points) to assess EMG stationarity. This length of segment was chosen as a compromise between feature variance, bias, and real-time constraints [9,10].

3.2.1. Variation of statistical properties

To investigate the hypothesis that the differencing of EMG time series can transform the original signal, $x(t)$, to be more stationary, variances in key statistical properties were investigated. A raw EMG time series of each motion trial was first divided into short analysis segments, and for each segment the mean and standard deviation were calculated. Then the variation of these quantities from all short segments in each motion trial was computed [2]. The EMG time series become more stationary when the variation of the statistical properties of EMG time series reduced [2,3].

In the preliminary study, the range of $d^{(1)}(t)$ values was narrower than the range of $x(t)$ values. Therefore, a normalized measure of statistical dispersion, the coefficient of variation (CV), was used instead of common measures such as variance or standard deviation. It is defined as the ratio of the standard deviation to the mean of the proposed quantity.

Two commonly used descriptive statistics are mean and standard deviation. However, raw EMG time series generally have a mean value of about zero, due to positive and negative deviations from baseline. In order to analyze EMG signals, TD features are usually preceded by full-wave rectification (making negative EMG values positive). Thus, the mean value was calculated from the rectified EMG signal instead of the raw signal [2]. On the other hand, the standard deviation of EMG signals is a function of muscle contraction level and can be calculated directly from raw EMG time series.

3.2.2. Reverse arrangements test

An evaluating test, namely the "reverse arrangements (RA) test" was used to evaluate the stationarity of forearm-muscle EMG signals at various hand, wrist, and forearm motions. The RA test has been widely used to evaluate the stationarity of surface EMG signals during static and dynamic contractions of upper- and lower-limb muscles [1,33]. It is important to note that the RA test is a general non-parametric test for a weak- or wide-sense stationarity [23]. The procedure of the RA test in which some parts are modified for this study is as follows:

(1) $x(t)$ is defined as the amplitude value of tth data point.
(2) The number of reverse arrangements (A) in the sequence $\{x(1), x(2), \ldots, x(N)\}$ are counted when $x(t) > x(i)$ for $t < i$. In other words, A is the number of times that the value of the first data point $x(1)$ in the segment is higher than each

Table 1 – Mathematical definitions of existing TD features extracted from $x(t)$ and $d^{(1)}(t)$.

Features extracted from x(t)	Features extracted from $d^{(1)}(t)$
$\mathrm{IEMG} = \sum_{t=1}^{N} \lvert x(t) \rvert$	$\mathrm{WL} = \sum_{t=1}^{N-1} \lvert x(t+1) - x(t) \rvert$
$\mathrm{MAV} = \frac{1}{N}\sum_{t=1}^{N} \lvert x(t) \rvert$	$\mathrm{DAMV} = \frac{1}{N-1}\sum_{t=1}^{N-1} \lvert x(t+1) - x(t) \rvert$
$\mathrm{SSI} = \sum_{t=1}^{N} x(t)^2$	$\mathrm{M2} = \sum_{t=1}^{N-1} (x(t+1) - x(t))^2$
$\mathrm{VAR} = \frac{1}{N-1}\sum_{t=1}^{N} x(t)^2$	$\mathrm{DVARV} = \frac{1}{N-2}\sum_{t=1}^{N-1} (x(t+1) - x(t))^2$
$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N} x(t)^2}$	$\mathrm{DASDV} = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N-1} (x(t+1) - x(t))^2}$
$\mathrm{MYOP} = \frac{1}{N}\sum_{t=1}^{N} [f(\lvert x(t) \rvert)];$	$\mathrm{WAMP} = \sum_{t=1}^{N-1} [f(\lvert x(t+1) - x(t) \rvert)];$
$f(a) = \begin{cases} 1, & \text{if } a \geq thr \\ 0, & \text{otherwise} \end{cases}$	$f(a) = \begin{cases} 1, & \text{if } a \geq thr \\ 0, & \text{otherwise} \end{cases}$

subsequent data point value, $x(2)$, $x(3)$, ..., $x(N)$, and then this process is repeated for $x(2)$, $x(3)$, ..., $x(N-1)$.

(3) The z-score is calculated using the following equation:

$$z = \frac{A - \left[\frac{N(N-1)}{4}\right]}{\sqrt{\frac{2N^3+3N^2-5N}{72}}}. \tag{1}$$

(4) The averaged absolute value of the z-score of all segments and motions for each trial is calculated and used to indicate the stationarity of EMG time series. A significant level is usually defined and then the signal stationarity is examined. The segment is stationary when the absolute value of the z-score is less than 1.96 for a 5% significant level, as used in previous studies [1,23]. However, in current study, the average absolute z-score values of time series $x(t)$ and $d^{(1)}(t)$ were directly compared.

3.3. Existing EMG features using a differencing technique

The success of any EMG pattern recognition system depends almost entirely on the selection of EMG features. Features based on time statistics have been widely used in research and can be performed within real-time constraints using simple hardware as compared to frequency-domain and time–frequency methods [7,10,34].

TD features calculated based on statistics of the original signal, $x(t)$, are (1) IEMG, (2) MAV, (3) SSI, (4) the variance of EMG (VAR), (5) RMS, and (6) MYOP, while matched TD features calculated based on the statistics of the transformed signal, $d^{(1)}(t)$, are (1) WL, (2) DAMV, (3) M2, (4) the difference variance value (DVARV), (5) DASDV, and (6) WAMP. Mathematical definitions of the proposed existing features are shown in Table 1. The threshold, thr, is a predefined threshold which is used to avoid background noise during EMG recording in the signal and was set at 20 for MYOP and WAMP based on the preliminary study. It should be noted that in several previous studies the DAMV was called "average amplitude change" [35].

3.4. Novel EMG features using a differencing technique

Five commonly used features that have not previously been applied to $d^{(1)}(t)$ were investigated for their classification performance in the current study including: (1) the absolute value of the higher order temporal moments (TM), (2) v-order (V), (3) log detector (LD), (4) autoregressive coefficients (AR), and (5) cepstrum coefficients (CC) [26,34,36]. There exist features other than the five mentioned above, including: mean absolute value slope, the EMG histogram, kurtosis, and skewness [26,37,38], however their classification accuracies are generally very low. Therefore, the results of such features are not included in this study. The five features extracted from both $x(t)$ and $d^{(1)}(t)$ were computed and compared based on their classification performance. To indicate which features were extracted from $x(t)$ and $d^{(1)}(t)$, the abbreviation of modified features is written beginning with "D". For example, the TM feature extracted from $x(t)$ is referred to as the DTM feature when extracted from $d^{(1)}(t)$. Mathematical definitions of the proposed features are shown as follows:

$$\mathrm{TM} = \left| \frac{1}{N}\sum_{t=1}^{N} x(t)^m \right|, \tag{2}$$

$$\mathrm{V} = \left(\frac{1}{N}\sum_{t=1}^{N} x(t)^v \right)^{1/v}, \tag{3}$$

$$\mathrm{LOG} = e^{\frac{1}{N}\sum_{t=1}^{N} \log(x(t))}, \tag{4}$$

$$x(t) = -\sum_{p=1}^{P} a(p)x(t-p) + w(t), \tag{5}$$

$$c(1) = -a(1); \quad c(p) = -a(p) - \sum_{l=1}^{p-1} \left(1 - \frac{l}{p}\right) a(P)c(p-l)$$
$$\text{for } 1 \leq l \leq P, \tag{6}$$

where m is the temporal moment order, v is the v order, P is the AR order or the CC order, $a(p)$ is autoregressive coefficients, $w(t)$ is a white noise error, $c(p)$ is cepstrum coefficients. Based on the preliminary experiments, m, v, and P were set at 3, 3, and 4, respectively.

3.5. EMG classification

In this study, the quality of EMG features was evaluated by the classification rates obtained from classifiers. Generally, classification accuracy is used as the main index to show the performance of EMG pattern recognition [39]. It is defined as the rate of correct classification to all analysis segments in a test set. Six classifiers including LDA, QDA, kNN ($k = 5$ [25]), decision tree (DT), naive Bayes (NB), and Mahalanobis distance (MD) were chosen as the representative classifiers in this study because the classification performance of these classifiers is not greatly dependent on the optimizing structures and parameters of the classifiers as it is with ANN and SVM classifiers. Six different classifiers were deployed to guarantee that the classification results did not depend on the type of classifiers. A single classification accuracy was produced by averaging across the 10-fold cross-validations for each subject. Original EMG datasets were randomly partitioned into 10 equal size sub-datasets. In each fold, a single sub-dataset was retained as testing data and the remaining 9 sub-datasets were used as training data for the classification model. The cross-validation process was then repeated 10 times using each sub-dataset once for training.

In order to perform a continuous classification, a class decision has to be analyzed and produced on a short analysis segment less than 300 ms, which is widely used as an acceptable delay for a real-time myoelectric control system [9,10]. However, segments shorter than this should be avoided since it can result in high variability for feature extraction [40]. There are two major techniques in data windowing: an adjacent (or disjoint) windowing and an overlapped windowing [11,41]. Processing time for either method is usually less than 50 ms [9], particularly for TD methods. To use the adjacent windowing technique, the length of an analysis segment may be up to approximately 250 ms in duration. Generally, this maximum segment length (under acceptable delay) could improve classification results as compared to a shorter segment length, e.g. 125 and 62.5 ms [17]. For the overlapped windowing technique, the segment length was set at 250 ms (256 samples at a 1024-Hz sampling rate) with the increment of 125, 62.5, and 31.25 ms (or 128, 64, 32 samples). In total, six conditions of data windowing were proposed (segment length/segment increment, in samples): 64/64, 128/128, 256/256, 256/128, 256/64, and 256/32.

4. Results and discussion

4.1. EMG stationarity tests

Generally, when TD features are used in the analysis of dynamic motions, the stationarity of surface EMG signals is presumed rather than specifically known [2]. Although, the investigation of surface EMG signal stationarity has been presented in many studies [1,2,33,42–46], a general consensus of the stationarity of surface EMG signals is yet to be reached because not only can the analysis segment length and muscle contraction type factors influence the stationarity of surface EMG signals, but the different stationarity tests can potentially lead to contradicting results. The stationarity tests used in previous studies such as the runs test, the RA test, or the modified RA test, may be not appropriate for examining the stationarity of EMG signals [33]. Therefore, in the present study the stationarity of surface EMG signals was not directly examined and discussed, but rather the stationary levels of EMG with and without applying the differencing technique were compared. More discussions about the EMG stationarity tests including segment length effect can be found in [1,33].

The first purpose of this study was to examine the stationarity of EMG time series with and without the differencing technique. The results of the three stationarity tests are presented in Table 2. Average CV for eight motions, calculated from time series $x(t)$ and $d^{(1)}(t)$, were compared by counting the number of trials in which the CV of the proposed quantity of $d^{(1)}(t)$ was lower than the CV of the proposed quantity of $x(t)$. For the RA test, the number of trials in which the average absolute z-score value of $d^{(1)}(t)$ was lower than the average absolute z-score value of $x(t)$ were counted.

In support of the first hypothesis, the results of the current study show that $d^{(1)}(t)$ becomes more stationary compared to $x(t)$. The number of trials from all the proposed tests were close to 60. The average number of trials from all subjects, muscles, motions, and tests were more than 55. It means that more than 92% of the transformed EMG signal segments become more stationary compared to the original measured signals (in detail, the coefficient of variation of mean-values test: 93% (55.85), the coefficient of variation of SD-values test: 96.2% (57.72), and the RA test: 99.58% (59.75)). In other words, it means that the differencing technique seems to make the surface EMG signals more stationary.

If the EMG time series $d^{(1)}(t)$ is more stationary than the EMG time series $x(t)$, TD features extracted from $d^{(1)}(t)$ should result in a higher degree of cluster separability than TD features extracted from $x(t)$, which would improve the classification accuracy. These results support previous studies [21,26] which suggest that an intra-class variation in feature space of $d^{(1)}(t)$ features such as WL, DAMV, and DASDV was lower than the intra-class variation of $x(t)$ features such as IEMG, MAV, and RMS.

It is important to note that three proposed stationarity tests can detect the non-stationarity caused by time-varying mean and/or variance, not time-varying frequency content [23]. However, the current study only focused on TD features. Although Beck et al. [33] reported that the RA test is inaccurate (i.e., some false positive and false negative cases) for assessing stationarity of some simulated signals and isokinetic EMG signals, the RA test has been shown to be a useful tool to assess the surface EMG signal stationarity of many muscles and motions in other previous studies [1,42–46]. In the present investigation, the RA test provided the similar results to the analysis of statistical properties' variations.

4.2. Existing EMG features using a differencing technique

The distributions of features extracted from the summation and the mean of EMG time series are quite similar [26], however, when estimating EMG amplitude, mean feature is preferred [47]. Therefore, only results of the mean features were reported: MAV and DAMV instead of IEMG and WL as well as VAR and DVARV instead of SSI and M2.

The second purpose of this study was to re-evaluate the classification performance of both $d^{(1)}(t)$ and $x(t)$ features using six different classifiers.

An analysis segment length of 256 samples incremented by 256 samples was utilized when extracting the existing features in Table 1. The achieved classification rates were computed from six different classifiers, and were averaged across all subjects for each feature and classifier, as shown in Table 3. In support of our hypothesis, and consistent with previous studies, the results of the current study show that

Table 2 – The stationarity of EMG time series between $x(t)$ and $d^{(1)}(t)$.

Subject	Number of trials that the CV of mean of $d^{(1)}(t)$ is lower than $x(t)$					Number of trials that the CV of SD of $d^{(1)}(t)$ is lower than $x(t)$					Number of trials that the z-score of $d^{(1)}(t)$ is lower than $x(t)$				
	ECRL	ECU	EDC	FCR	Mean	ECRL	ECU	EDC	FCR	Mean	ECRL	ECU	EDC	FCR	Mean
1	60	53	57	60	57.50	60	56	59	60	58.75	60	60	60	60	60
2	59	60	60	60	59.75	60	60	60	60	60	59	60	60	60	59.75
3	58	27	49	58	48	56	40	51	59	51.50	60	60	59	60	59.75
4	58	58	60	60	59	57	59	60	60	59	60	59	59	60	59.50
5	60	60	59	60	59.75	60	59	59	60	59.50	60	60	60	60	60
6	47	39	45	59	47.50	52	49	49	60	52.50	60	60	60	59	59.75
7	60	60	60	60	60	60	60	60	60	60	60	60	59	60	59.75
8	60	56	60	58	58.50	60	57	60	57	58.50	60	60	60	60	60
9	59	56	54	59	57	59	59	57	59	58.50	60	58	60	60	59.50
10	56	51	51	55	53.25	58	58	58	57	57.75	59	60	58	57	58.50
11	60	60	60	59	59.75	60	60	60	59	59.75	60	60	60	60	60
12	60	52	60	59	57.75	60	58	60	58	59	60	60	60	60	60
13	55	34	51	45	46.25	57	50	57	53	54.25	60	59	60	60	59.75
14	60	60	57	60	59.25	60	60	59	60	59.75	60	60	60	60	60
15	60	52	59	60	57.75	60	55	60	60	58.75	60	60	60	60	60
16	60	60	57	60	59.25	60	60	58	60	59.50	60	60	60	60	60
17	52	44	35	52	45.75	54	55	47	54	52.50	60	57	60	60	59.25
18	60	57	60	60	59.25	60	59	59	60	59.50	60	60	60	60	60
Mean	58	52.17	55.22	58	55.85	58.50	56.33	57.39	58.67	57.72	59.89	59.61	59.72	59.78	59.75

Table 3 – Mean classification accuracies (and their standard deviations in brackets) of the existing features based on $x(t)$ and $d^{(1)}(t)$ using six different classifiers with a segment length condition 256/256.

Feature		Classifier						
		LDA	QDA	kNN	DT	NB	MD	Total
MAV	$x(t)$	78.98 (7.3)	84.88 (8.0)	85.23 (7.6)	78.82 (8.0)	69.76 (10.4)	83.15 (8.4)	80.14 (8.3)
DAMV	$d^{(1)}(t)$	83.33 (6.4)	90.12 (5.9)	89.60 (5.5)	84.07 (6.6)	77.31 (8.5)	87.95 (7.1)	85.40 (6.7)
VAR	$x(t)$	62.56 (8.2)	75.65 (10.1)	81.59 (7.3)	78.48 (8.0)	59.32 (13.0)	75.66 (9.3)	72.21 (9.3)
DVARV	$d^{(1)}(t)$	69.58 (7.0)	85.23 (6.8)	86.40 (5.8)	83.57 (6.2)	71.20 (10.2)	82.84 (7.9)	79.80 (7.3)
RMS	$x(t)$	78.00 (7.5)	83.50 (8.2)	84.65 (7.6)	78.50 (8.0)	67.71 (11.0)	82.24 (8.5)	79.10 (8.5)
DASDV	$d^{(1)}(t)$	83.16 (6.4)	89.42 (5.8)	89.23 (5.4)	83.59 (6.0)	76.17 (8.8)	87.78 (6.9)	84.89 (6.5)
MYOP	$x(t)$	76.31 (8.9)	79.20 (9.3)	78.25 (10.1)	75.28 (9.6)	68.86 (10.2)	78.42 (9.4)	76.05 (9.6)
WAMP	$d^{(1)}(t)$	82.81 (7.6)	85.48 (7.2)	85.14 (7.4)	79.26 (7.5)	74.90 (8.8)	84.61 (7.5)	82.03 (7.7)

EMG features extracted from $d^{(1)}(t)$: DAMV, DVARV, DASDV, and WAMP, provide better classification accuracy compared to features extracted from $x(t)$: MAV, VAR, RMS, and MYOP. On average, classification accuracies of the proposed features were improved by 5–8% by applying the differencing technique. One-way analysis of variance (ANOVA) was used to analyze the statistically significant differences between the mean classification rates of $x(t)$ and $d^{(1)}(t)$ features across 18 subjects. Statistically significant differences ($p < 0.001$) were found for all features and classifiers, as shown in Table 3. The classification accuracies of $d^{(1)}(t)$ features also exhibited less fluctuation, as can be observed from lower standard deviation values of the classification rates in Table 3.

In Fig. 1, the confusion matrices of MAV and DAMV show that the differencing technique improved the classification performance of all movement classes. Moreover, the performance improvement for features extracted from $d^{(1)}(t)$ over $x(t)$ was not dependent on the classifier type. The QDA classifier gave the best classification results compared to other classifiers, so only results of the QDA classifier are reported for the remaining analyses.

Classification rates were computed by using only the QDA classifier, but features were extracted from six different conditions of data windowing, as shown in Table 4. The classification accuracies achieved by $d^{(1)}(t)$ features were higher than $x(t)$ features for all analysis window conditions, and statistically significant differences ($p < 0.001$) were found for all features and segment conditions in Table 4. Moreover, performance improvements for features extracted from $d^{(1)}(t)$ over $x(t)$ were not dependent on segment conditions.

The DAMV feature exhibited the best performance with an overall classification accuracy of 95.82%, when the QDA classifier with an analysis segment length of 256 samples incremented by 32 samples was used, followed closely by DASDV, DVARV, and WAMP with 95.57%, 93.92%, and 92.04%, respectively.

As a single feature in an input vector for a classifier cannot reach the best performance in the classification of dynamic motions associated with surface EMG signals, and only one value per EMG channel can be obtained from all the studied features, all proposed $d^{(1)}(t)$ features would be combined to create a more powerful feature vector in future studies. Moreover, both feature groups share more distribution within the EMG feature space [26,48], so $d^{(1)}(t)$ features: DAMV, DVARV, DASDV, and WAMP are recommended instead of traditional $x(t)$ features: MAV, VAR, RMS, and MYOP.

4.3. *Novel EMG features using a differencing technique*

The achieved classification accuracies of five features extracted from $x(t)$ and $d^{(1)}(t)$ are shown in Table 5, which were computed from the QDA classifier with the segment length condition 256/32. All features extracted from $d^{(1)}(t)$ always gave higher classification rates than features extracted from $x(t)$. Overall classification rates were increased by 1.3% for AR to 7.4% for TM by applying the differencing technique, and statistically significant differences ($p < 0.005$) were found for all features in Table 5.

Among five features, the DAR has the best overall performance (97.76%), followed closely by the DCC (97.51%). Although other modified features: DTM, DV, and DLD provided lower classification rates than the existing $d^{(1)}(t)$ features such as DAMV and DASDV and the modified $d^{(1)}(t)$ features such as DAR and DCC, these features should be considered for inclusion in a feature vector due to the different distribution in feature space and properties [26].

In addition to applying the differencing technique, to increase the inter-class distance and decrease the intra-class variation, a logarithm transformation was proposed to $d^{(1)}(t)$ features. For example, applying the logarithm transformation to DAMV and DASDV can be defined as follows:

$$\log\ \mathrm{DAMV} = \log\left(\frac{1}{N}\sum_{t=1}^{N-1}\left|x(t+1)-x(t)\right|\right), \tag{7}$$

$$\log\ \mathrm{DASDV} = \log\left(\sqrt{\frac{1}{N-1}\sum_{t=1}^{N-1}(x(t+1)-x(t))^2}\right). \tag{8}$$

Mean classification accuracies obtained from the QDA classifier with the segment length condition 256/32 of the log DAMV was 96.32% (3.1%) compared to DAMV 95.82% (3.3%) and the log DASDV was 95.98% (3.2%) compared to DASDV 95.57% (3.4%). No statistically significant difference was found between mean classification rates of features with and without the logarithm transformation ($p > 0.1$). In previous studies [49], the logarithm and differencing transformations were applied as parts of the maximum fractal length (MFL) method. The definition of MFL resembles a modified version of IEMG by using the differencing and logarithm transformations when the smallest scale was set at 1 and can also be defined as

Table 4 – Mean classification accuracies (and their standard deviations in brackets) of the existing features based on $x(t)$ and $d^{(1)}(t)$ using the QDA classifier with six different segment length conditions: 64/64, 128/128, 256/256, 256/128, 256/64, and 256/32.

Feature		Segment length condition						
		64/64	128/128	256/256	256/128	256/64	256/32	Total
MAV	$x(t)$	72.94 (9.9)	79.25 (10.3)	84.88 (8.0)	85.86 (8.3)	87.92 (7.0)	92.53 (6.0)	83.90 (8.2)
DAMV	$d^{(1)}(t)$	81.08 (7.4)	85.93 (7.6)	90.12 (5.9)	90.97 (5.8)	92.78 (4.6)	95.82 (3.3)	89.45 (6.3)
VAR	$x(t)$	63.58 (11.6)	68.52 (12.4)	75.65 (10.1)	76.86 (11.2)	81.72 (9.4)	88.87 (7.7)	75.87 (10.4)
DVARV	$d^{(1)}(t)$	74.50 (8.3)	80.05 (8.9)	85.23 (6.8)	86.17 (7.8)	89.26 (6.4)	93.92 (4.5)	84.86 (7.1)
RMS	$x(t)$	72.26 (9.9)	78.20 (10.3)	83.50 (8.2)	84.40 (8.7)	87.02 (7.1)	91.72 (6.1)	82.85 (8.4)
DASDV	$d^{(1)}(t)$	80.40 (7.1)	85.17 (7.7)	89.42 (5.8)	90.27 (6.0)	92.25 (4.6)	95.57 (3.4)	88.85 (5.8)
MYOP	$x(t)$	64.17 (10.5)	72.47 (11.0)	79.20 (9.3)	80.91 (9.5)	82.69 (8.4)	87.33 (7.8)	77.86 (9.4)
WAMP	$d^{(1)}(t)$	72.54 (8.6)	79.73 (8.9)	82.81 (7.6)	86.39 (7.5)	88.18 (6.2)	92.04 (5.1)	83.62 (7.3)

Table 5 – The classification accuracies (and their standard deviations in brackets) of the novel features based on $x(t)$ and $d^{(1)}(t)$ using the QDA classifier with a segment length condition 256/32.

EMG data	Feature				
	TM	V	LD	AR	CC
$x(t)$	82.12(9.9)	90.24 (6.6)	90.20 (6.8)	96.40 (1.8)	91.23 (4.2)
$d^{(1)}(t)$	89.58(6.6)	94.40 (4.0)	93.20 (4.6)	97.76 (1.1)	97.51 (1.2)

log WL. Based on current results, a logarithm transformation does not appear to improve accuracies.

5. Limitations

Limitations to the current research study are acknowledged. First, we did not investigate the utility of higher-order derivatives on the EMG signal features. Khushaba et al. [28] proposed several novel EMG features based on the first- and second-order differences of EMG time series and reported low classification error rates (approximately 10%) in the recognition of eight motions regardless of the limb position. Future research is needed in this area to better understand the utility of higher-order derivatives on the EMG signal features. Second, it is commonly observed that differentiating any signal degrades the signal-to-noise ratio (SNR). In current study, the lowest SNR of the time series $x(t)$ was 25.5 dB while the lowest SNR of the time series $d^{(1)}(t)$ was only 24.5 dB for all motions and muscles. No statistically significant difference of SNRs between $x(t)$ and $d^{(1)}(t)$ was found ($p > 0.1$). In this study, noise was calculated from the signal during rest state or no movement, measured at the beginning and ending of each session. Future studies should consider analysis of surface EMG signal at low SNR level associated with specific movements and muscles. Moreover, the effect of higher-order derivatives on the SNR level of the signal needs to be examined. Finally, we did not collect EMG signals from amputees or elderly subjects and thus these information was not included in the analysis. Although the current results may hold for amputees or elderly subjects, future studies should also incorporate EMG data measured from young and elderly subjects as well as normal and amputee subjects in the analysis to gain a greater understanding of the differences between subjects of interest.

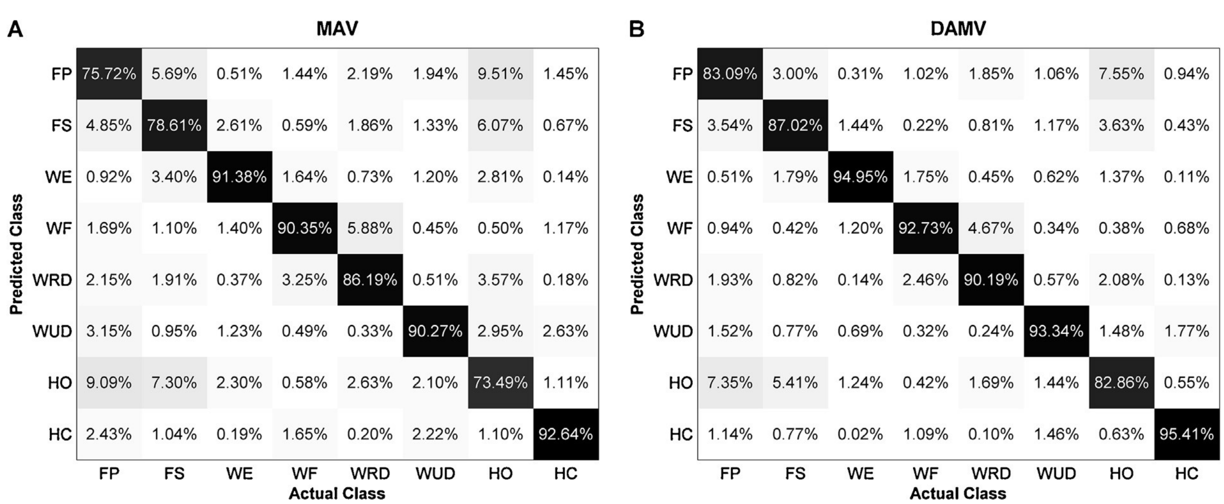

Fig. 1 – Confusion matrices of (A) MAV and (B) DAMV features, across all subjects.

6. Conclusions

In conclusion, features extracted from the first difference of EMG time series are recommended for use in the classification of motions associated with surface EMG signal instead of features extracted from the original measured EMG signals. As a result of the proposed technique, the within-class variation of features extracted from the transformed EMG signal decreases, while it is possible to preserve the distance of clusters between classes. The findings in this study can be applied in many EMG applications including muscle–computer interfaces. In future studies, multiple EMG features based on the differencing technique, for example, DAMV, DASDV, WAMP, DAR, and DCC should be investigated and optimized together with successful classifiers such as the SVM, ANN, QDA, and LDA classifiers.

Conflict of interest

The authors declared that there is no conflict of interest.

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