Improving the Performance against Force Variation of EMG Controlled Multifunctional Upper-Limb Prostheses for Transradial Amputees

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***Abstract*—We investigate the problem of achieving robust control of hand prostheses by the Electromyogram (EMG) of transradial amputees in the presence of variable force levels, as these variations can have a substantial impact on the robustness of the control of the prostheses. We also propose a novel set of features that aim at reducing the impact of force level variations on the prosthesis controlled by amputees. These features characterize the EMG activity by means of the orientation between a set of spectral moments descriptors extracted from the EMG signal and a nonlinearly mapped version of it. At the same time, our feature extraction method processes the EMG signals directly from the time-domain to reduce computational cost. The performance of the proposed features is tested on EMG data collected from nine transradial amputees performing six classes of movements each with three force levels. Our results indicate that the proposed features can achieve significant reductions in classification error rates in comparison to other well-known feature extraction methods, achieving improvements of ≈6% to 8% in the average classification performance across all subjects and force levels, when training with all forces.**

***Index Terms*— Classification, Force level variation, Myoelectric control, Pattern recognition, Robustness, Surface Electromyogram (sEMG), Transradial amputees.**

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I. INTRODUCTION

IN the United States, there are nearly 2 million people living with limb loss [1] with approximately 185,000 amputations occurring every year [2]. The main causes for limb loss include vascular disease (54%) and trauma (45%) with upper-limb amputations accounted for the vast majority (68.6%) of all trauma-related amputations, according to the statistics of National Limb Loss Information Centre [3].

Many advances were achieved during the past decades in the development of multifunctional upper limb prostheses controlled with EMG. These include advanced research hands [4]–[7] and commercially available hands [8]–[11], both employing conventional myoelectric control strategies [12]. In addition, advanced control techniques such as Pattern Recognition (PR) based EMG control[13], [14] and regression techniques[14], [15] were also proposed and investigated. However, no prosthesis is available in the market that has the capability to perform multiple functions with reliable performance. This is partially due to a big gap between academia and industry, which limits the clinical implementation of prostheses for amputee use. The impact of such a gap is anticipated to continue expanding unless a change of focus in myoelectric control systems occurs [16]. The lack of intuitive control, poor system reliability and the lack of robustness against practical problems were all identified as outstanding obstacles contributing to this gap [14], [16]. Nowadays, researchers in this field are mainly focused on tackling the practical problems, that may impact the robustness and reliability during daily life usage of PR systems, such as different arm positions or arm postures[17]–[20], electrode shift [21], [22], signal non-stationarity [23], and force variation [13].

The effect of the variation in the force of contraction on hand movement classification has received little attention, with most studies focusing on evaluating the performance on intact-limbed subjects rather than the amputees. The signature of the EMG signal changes with varying force levels due to modifications in the EMG time-frequency characteristics and the probability density function [24], [25]. These changes may degrade the performance of the PR system, which may fail to produce the proper decision for a particular movement.

Tkach *et al.* [26] studied the stability of Time Domain (TD) features with a Linear Discriminant Analysis (LDA) classifier during low and high forces with EMG signals collected from only intact-limbed subjects for four forearm movements. They found that training the classifier with low force or with combined low and high forces provided better accuracy than when training the classifier with only the high level of force. However, they did not include the medium force level to investigate the variability of the signals for a given movement. Moreover, hand and finger movements were not investigated, which are the main movements needed by the transradial amputees for prosthesis control[27].

In [13], the effect of force level variation on the performance of PR based EMG control was investigated for intact-limbed subjects who performed 9 classes of hand motion. The force level varied from 20% to 80% of the maximum voluntary contraction. TD features and an LDA classifier were also used for classification. To test the ability of the PR system to handle new forces, the classifier was trained with each force level, and then tested with all force levels. The classification error rates were between 32% and 44%, compared to 8-19% when training and testing with the same force level. The high error rates when testing with the unseen forces reflect the importance of the problem of force variation, which will render the PR system unusable at all.

In [28], three force levels were measured (30%, 60% and 90% of the maximum long term voluntary contraction) for only intact-limbed subjects. All force levels were included in the training and testing. However, testing with individual force levels in order to examine the effect of changing the force on the classification performance was not performed.

Recently, a feature extraction method based on discrete Fourier transform and muscle coordination was proposed by He *et al.*[29] and applied to EMG data collected from intact-limbed subjects who performed nine wrist movements with three different force levels. The classification accuracy was increased by approximately 11% when using the proposed features compared to the TD feature set. However, a specific sensor-placement configuration, by which the EMG electrodes were attached on pre-specified forearm muscles, was reported as vital for the algorithm to perform well. This configuration is limited by the difficulty to place the electrodes on the deformed amputee stump, which may make it difficult to reproduce their results with the transradial amputees.

In most of the previous work, the experiments were conducted only on intact-limbed subjects who benefited from visual and proprioceptive feedback from the hand [13], [26], [29]. In real life, an amputee lacks both these feedbacks because of the loss of the limb after the amputation process. More importantly, it is not known if these findings can be generalized to amputees since they have a different muscle structure after amputation. In our pilot work [30], the effect of force variation on the PR system performance was investigated for two transradial amputees who performed only four hand movements. The results showed that the performance of the myoelectric control system is degraded by up to 60% when the force level varied and that TD features outperformed Autoregressive (AR) and root mean square features.

The dependency on the well-known time domain features and AR model parameters was also obvious in most of the previous studies in this direction, without thorough investigations into novel feature extraction methods. Achieving features invariant to force levels would be a remarkable breakthrough towards reliable control of hand prostheses with PR systems. This calls for a new method to control the force in measurements with amputees rather than relying on traditional methods from the literature. Previous research also necessitated training the classifiers with features from all anticipated force levels that the subject may exert during real-time testing [13], [26], [28], [30]. However, such a scheme has not been fully explored with different feature extraction methods while collecting the EMG signals from amputees. Thus, extracting a set of EMG features invariant to force level variations should also be investigated, preferably on amputees as they are the main persons in need for such robust technology.

Recently, Khushaba *et al.*[18] proposed a time-dependent spectral Feature Extraction (FE) method that extracts a set of power spectrum characteristics directly from the time-domain to reduce the impact of variation of limb position, while keeping a low computational cost. The proposed method achieved a significant reduction in classification error rates, in comparison to other traditional methods and it helped to improve the practical robustness against variation in limb position without the need for accelerometers as done in [17], [20]. However, this was only applied to EMG collected from intact-limbed subjects. The proposed spectral moments were also used in [31] to develop multi-

user myoelectric interfaces which can adapt to novel users and maintain good movement recognition performance.

This paper investigates the practical problem of variable force levels for PR-based systems when used by the amputees, and how to improve the practical robustness of the PR system against force variation with a proper training strategy and robust EMG features. More specifically, our contributions are: 1) A modified version of Khushaba *el al.*[18] spectral moments will be proposed to reduce the effect of forcevariation[18] and they will be compared to the traditional FE methods across nine transradial amputees; 2) A training strategy will be investigated in detail to help to decrease the effect of force change for the amputees.

II. Materials and Methods

A. The Proposed Feature Extraction Technique

The proposed novel feature extraction algorithm extends the recent work by Khushaba *et al.* [18], [32] in an attempt to form a set of invariants to force level variations in two steps. In the first step, a set of power spectrum moments are extracted directly from the time-domain signal using signal norms and derivatives in a similar manner to that in [18]. The main idea here is to reduce the computational cost required for spectral moment feature extraction by directly extracting these features from the time domain using Fourier transform (FT) relations and the Parseval's theorem. Unlike the works in[18] and [32], we also extract the power spectrum moments from a logarithmically scaled version of the EMG signal, a step which results in a modified form of the well-known cepstral feature extraction [34]. In addition, since the derivatives employed in the first step are known to be easily affected by noise, it is then important to normalize the extracted feature values to reduce the impact of noise. For this specific purpose, we employ a normalization step by raising the log-scaled-amplitudes to a suitable power[35], before implementing the second step in the feature extraction process, as will be explained in the next section.

In the second step, we employ the cosine similarity to estimate the orientation between the extracted power spectrum characteristics from the original EMG signals and their nonlinear cepstral version and employ the orientation vector as our proposed feature set. The full algorithm description is presented in the next section.

1) Time-Dependent Power Spectrum Descriptors (TD-PSD)

Given a sampled version of the EMG signal denoted as $x[j]$, with j=1,2,…N, of length N and a sampling frequency fs Hz, the EMG trace within a certain epoch can be expressed as a function of frequency $X[k]$ by means of Discrete Fourier transform (DFT). We start the feature extraction process by observing Parseval's theorem which states that the sum of the square of the function is equal to the sum of the square of its transform

$$\sum_{j=0}^{N-1} |x[j]|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X[k]X^*[k]| = \sum_{k=0}^{N-1} P[k] \quad \ldots(1)$$

where $P[k]$ is the phase-excluded power spectrum, i.e., the result of a multiplication of $X[k]$ by its conjugate $X^*[k]$ divided by N, and k is the frequency index. It is generally well-known that the complete frequency description as derived by means of the Fourier transform is symmetric with respect to zero frequency, i.e., it has identical branches stretching into both positive and negative frequencies [36]. As a consequence of this symmetry and because we have no direct access to the power spectral density from the time-domain then we are left with the option of dealing with the whole spectrum, including positive and negative frequencies. Thus, in a statistical approach to the shape of the frequency distribution, all odd moments will become zero, according to the definition of a moment m of order n of the power spectral density $P[k]$ which is given by

$$m_n = \sum_{k=0}^{N-1} k^n P[k] \quad \ldots(2)$$

In the above equation, when n=0 we will make use of Parseval's theorem in Eq.(1), and for non-zero values of n we will use the time-differentiation property of the Fourier transform. Such a property simply states that the n^{th} derivative of a function in the time-domain, denoted as Δ^n for discrete time signals, is equivalent to multiplying the spectrum by k raised to the n^{th} power

$$F\left[\Delta^n x[j]\right] = k^n X[k] \quad \ldots(3)$$

To this end, we define the features utilized in this paper as shown in Fig.1:

- **Root squared zero order moment ($\bar{m}_0$):** A feature that indicates the total power in the frequency-domain, or simply the strength of muscle contraction, which is given as

$$\bar{m}_0 = \sqrt{\sum_{j=0}^{N-1} x[j]^2} \quad \ldots(4)$$

The resultant zero order moments from all of the channels can also be normalized by division by the sum of the zero order moments from all of the channels.

- **Root squared second and fourth order moments:** according to Hjorth [36] the second moment can be considered as a power, but then of a modified spectrum $k^2P[k]$, corresponding to a frequency function

$$\bar{m}_2 = \sqrt{\sum_{k=0}^{N-1} k^2 P[k]} = \sqrt{\frac{1}{N}\sum_{k=0}^{N-1} (kX[k])^2} = \sqrt{\sum_{j=0}^{N-1} (\Delta x[j])^2} \quad \ldots(5)$$

A repetition of this procedure gives the moment.

$$\bar{m}_4 = \sqrt{\sum_{k=0}^{N-1} k^4 P[k]} = \sqrt{\sum_{j=0}^{N-1} (\Delta^2 x[j])^2} \quad \ldots(6)$$

In this case, taking the second and fourth derivatives of the signal reduces the total energy of the signal; hence, we apply a power transformation to normalize the range of $m_0, m_2,$ and $m_4$and to reduce the effect of noise on all moments based features as follows

$$\begin{aligned} m_0 &= \frac{\bar{m}_0{}^{\lambda}}{\lambda} \\ m_2 &= \frac{\bar{m}_2{}^{\lambda}}{\lambda} \\ m_4 &= \frac{\bar{m}_4{}^{\lambda}}{\lambda} \end{aligned} \quad \ldots(7)$$

With λ empirically set to 0.1. The first three extracted features from these variables are then defined as.

$$f_1 = \log(m_0)$$
$$f_2 = \log(m_0 - m_2) \quad \ldots(8)$$
$$f_3 = \log(m_0 - m_4)$$

- **Sparseness**: this feature quantifies how much energy of a vector is packed into only a few components. It is given as

$$f_4 = \log\left(\frac{m_0}{\sqrt{m_0 - m_2}\sqrt{m_0 - m_4}}\right) \quad \ldots(9)$$

Such a feature describes a vector with all elements equal with a sparseness measure of zero, i.e., m_2 and m_4 =0 due to differentiation and $\log(m_0/m_0)$=0, whereas for all other sparseness levels, it should have a value bigger than zero[18].

- **Irregularity Factor (*IF*)**: a measure that represents the ratio of the number of upward zero crossings divided by the number of peaks. According to [37], the number of upward zero crossings (*ZC*) and the number of peaks (*NP*) in a random signal can be expressed solely in terms of their spectral moments. The corresponding feature can be written as

$$f_5 = \frac{ZC}{NP} = \frac{\sqrt{\frac{m_2}{m_0}}}{\sqrt{\frac{m_4}{m_2}}} = \sqrt{\frac{m_2^2}{m_0 m_4}} = \frac{m_2}{\sqrt{m_0 m_4}} \quad \ldots(10)$$

- **Waveform Length Ratio (*WL*)**: Given the definition of the waveform length feature as the summation of the absolute value of the derivative of the signals, then we define our *WL* feature as the ratio of the waveform length of the first derivative to that of the waveform length of the second derivative.

$$f_6 = \log\left(\frac{\sum_{j=0}^{N-1}|\Delta x|}{\sum_{j=0}^{N-1}|\Delta^2 x|}\right) \quad \ldots(11)$$

The waveform length feature was shown to be very relevant for EMG classification tasks[38]. However, the proposed *WL* feature further extends the work in the literature to form a feature that is invariant to amplitude scaling.

Fig. 1. Block diagram of the proposed feature extraction process.

According to the schematic in Fig. 1, we first extract the proposed six features from each EMG record x and form a vector denoted as $\mathbf{a} = [a_1, a_2, a_3, a_4, a_5, a_6]$. An additional feature vector, denoted as $\mathbf{b} = [b_1, b_2, b_3, b_4, b_5, b_6]$ is then extracted from a logarithmically scaled version log (x^2) to end up with two feature vectors: **a** (from the EMG record) and **b** (from a nonlinearly scaled version of the EMG record), each made up of 6 elements. Our final features, being 6 extracted features per each EMG channel, are then extracted as the orientation of the two vectors given by a cosine similarity measure as defined below

$$f_i = \frac{-2\, a_i b_i}{{a_i}^2 + b^2}, \qquad i = 1,2,3, \ldots 6 \qquad \ldots(12)$$

The features represented by the resultant vector **f** are used in the classification process. These features can be thought of as a type of cepstral representation of the EMG activity. However unlike the well-known speech cepstral features (a nonlinear spectrum-of-a-spectrum or the inverse FFT of the logarithm of the spectrum, depending on the implementation [34]), we derived our EMG features as the orientation between the features extracted from a nonlinearly mapped EMG record and the original EMG record according to Eq.(12). Our main justification for not using **a** or **b** feature vectors directly as our resultant features is that feature vector **f** is less affected by the level of contraction efforts than **a** and **b** feature sets, as the resultant vector **f** is a measure of orientation and not magnitude. The orientation based feature extraction methods were recently shown to be of significant importance to the problem of EMG classification under varying force levels, when tested on intact-limbed subjects, as force production relies on the coordination of multiple hand muscles [29]. However, no previous experiments were made to test the effectiveness of such features on amputees. In the next subsections, we prove the suitability of the proposed orientation based feature set to classify the EMG signals, with variable forces levels, for the transradial amputees. In the rest of the paper, we denote our final feature set **f,** concatenated from all channels, as the Time-Dependent Power Spectrum Descriptors (TD-PSD).

B. Amputee Participants, Electrode Placement and Signal Acquisition

Nine transradial amputees (seven traumatic and two congenital) with unilateral amputation participated in this study. The details of the demographic information for each amputee are shown in Table1. The EMG datasets for amputees TR1-TR6 (Transradial 1 to 6) were collected at the Artificial Limbs and Rehabilitation Centres in Baghdad (Iraqi Army) and Babylon (Ministry of Health), Iraq, while the EMG datasets for TR7 (Transradial 7), CG1 (Congenital 1) and CG2 (Congenital 2) were collected at Plymouth University, UK. The local ethical committee at the School of Computing and Mathematics, Plymouth University approved this research. The aim of the experiments was explained to the participants, and they gave their written informed consent to participate in the study.TR1-TR7 did not wear myoelectric prosthesis while CG1 and CG2 used it for a certain time of their life.

Table 1. Demographic information of the amputees who participated in the study

ID	Age (y)	Sex	Type of Amp.	Missing hand	Stump length (cm)	Stump Cir (cm)	Time since Amp	Type of prosthesis
TR1	25	M	Traum	Left	13	27	4 years	Cos
TR2	33	M	Traum	Left	18	24	6 years	None
TR3	30	M	Traum	Left	29	23.5	28 years	COS
TR4	27	M	Traum	Left	16	23	4 years	BP
TR5	35	M	Traum	Left	23	26	8 years	Cos
TR6	29	M	Traum	Left	24	26	7 years	Cos
TR7	57	M	Traum	Left	14	27	3 years	None
CG1	19	F	Conge	Left	9	19	N/A	Myo 3-12y
CG2	31	F	Cong	Right	10.5	27	N/A	Myo 8-16 y

Cir= Circumference, Traum=Traumatic, Cong= Congenital, Amp=Amputation, Myo=Myoelectric, BP=Body Powered, Cos=Cosmetic

Before the placement of the sEMG electrodes, the skin of the subjects was cleaned with alcohol and abrasive skin preparation gel (NuPrep®, D.O. Waver and Company, USA) was applied. Eight pairs of Ag/AgCl electrodes (Tyco healthcare, Germany) connected to a differential amplifier were placed around the left stump in one or two rows for all amputees apart from CG2 where the electrodes were placed on the right stump. Fig. 2 shows the electrode locations for CG1 as an example. European recommendations for sEMG (SENIAM) were followed for placing the surface electrodes, and the elbow joint was used as reference to mark the electrode locations.

Fig. 2 . The surface electrodes locations for the amputees showing the left stump for CG1.

A custom-build, multi-channel EMG acquisition system was used to acquire the data at a sampling rate of 2000Hz. A virtual Instrument (VI) implemented in LABVIEW (National Instruments, USA) was used for signal acquisition and display. This was used by the amputees to help to produce the needed force level.

C. Experimental protocol

Six movements including different grip and finger movements were investigated in this paper. These movements were discussed with the amputees, and they thought that they may be important to them. The gestures are: 1) Thumb flexion; 2) Index flexion; 3) Fine pinch; 4) Tripod grip; 5) Hook grip (hook or snap); 6) Spherical grip (power).

To examine the effect of force variation on the performance of EMG-based PR systems, the following experimental protocol was used. After electrodes placement, each amputee was asked to examine the EMG signals on the screen in real-time and familiarize themselves with the changes in force of contraction for different movement. The objective was for them to see how the amplitude changed according to the force. They were given a couple of minutes to explore this.

It is very challenging for the amputee to produce a different force level of contraction for a given movement because of the loss of visual and proprioceptive feedback from the hand after the amputation. The aim was to record lower and higher levels of force than the moderate level of force that the prosthesis usually works with. This intended to simulate the daily life scenario when the force of contraction may vary with everyday use.

The amputees used their intact-hand to help them to imagine the needed movement with the required force. In addition, they used Visual Feedback (VF) from the Labview screen to see the EMG channels. This was useful for them to produce the needed force. It is worth mentioning that TR7 had diabetes mellitus, which caused the limb to be amputated. In addition, the participant was visually impaired with little vision capability, and he did not use glasses during the experiment. Instead, he used the intact-limb to help him to imagine the needed movement. In Fig. 3, TR5 is performing spherical grip with the help of the intact arm and VF from the EMG channels.

Fig.3 Amputee TR5 executing the protocol for recording different force levels. He used the VF and intact limb to produce the spherical grip, as it can be seen in the picture.

For each of the six grip patterns, the amputees produced three force levels: low, medium and high. For each force level, five to eight trials were recorded for each amputee where each trial is a holding phase lasting 8-12 seconds. Thus, the *total* number of trials performed by each amputee was equal to the number of movements× number of force levels ×number of trials for each movement.

The following protocol was used for the recording of 3 forces levels:

-Low Force: To record the EMG with different forces, each amputee was asked to produce the constant non-fatiguing contraction with "low level of force", which is lower than the usual moderate level and hold it for 8-12 seconds. It is worth noting that the amputees found the visual feedback very helpful in producing a low level of contraction.

-Moderate Force: In this step of the protocol, the amputees were asked to produce a moderate force level slightly higher than low level produced in the previous step, with constant non-fatiguing contraction with moderate force and hold the position for a period of 8-12 seconds for each movement.

-High Force: A higher than moderate force level was produced by the amputees with the help of visual feedback and the intact-hand. They were instructed to produce high force level at a comfortable level to them, and to hold the contraction for 8-12 seconds. The Maximum Voluntary Contraction (MVC) was avoided since it might have caused fatigue due to the non-use of the muscle for long time. Preliminary investigation with some amputees to produce MVC for a given movement on the same day of the experiment caused some pain and fatigue. For this reason, MVC was not included in the recording protocol.

In general, producing the low and high force levels was difficult for some amputees, as they had not used their remaining muscles in the stump for long time. Furthermore, the high force of the contraction produced a tremor on some occasions while performing the trial. It is worth noting CG1 had some muscle twitches while she was performing the experiment. She took a longer relaxation time than other amputees between the sessions in order to avoid fatigue. Fig.4 shows an example of

one trial EMG signal for one channel with 3 levels of forces (low, medium, and high) for spherical grip for the TR3.

Fig.4 Single trial of one channel EMG signal for TR3 for different levels of contraction for spherical grip gesture. A. Low force. B. Medium force. C. High force.

D. EMG pattern recognition Analysis

MATLAB® 2013a software (Mathworks, USA) was used to perform the analyses. An overlapped segmentation scheme was used with 150 ms segment length and 50 ms segment overlap. The average controller delay for this setting is 100+τ ms (τ is the processing time for each segment), calculated according to the new average controller delay equations proposed in [39]. This delay lies within the acceptable controller delay for the EMG controlled prosthesis[40].

An ideal feature set should be immune (or, at least, robust) to force change while maintaining a good class separability in order to be able to distinguish between many movements with multiple forces. First, we test the performance of our proposed TD-PSD feature set, against other well-known feature extraction methods from the literature. These include:

1)Reduced spectral moments by Vuskovic and Du (denoted as VD-MOM) [41];

2) Time-domain features (denoted as TD) [13]which contain the following: integral absolute value, waveform length, zero crossings, slope sign changes, and kurtosis. It was shown that kurtosis is a good measure to characterize the force level changes based on an analysis of the probability density function of the EMG signal [24] and it has been used in the literature with EMG signals. For that reason, kurtosis was added to the TD feature set.

3) A combination of time-domain and Autoregressive model parameters, with an AR model order of 5, (denoted as AR+RMS) [42]; and

4) Wavelet features, represented by the energy of the coefficients at each node of Symmlet-8 family tree with 5 levels decomposition with the wavelet family and the decomposition levels chosen empirically.

The total number of features for each force level was 48, apart from the TD set which had 40 features (number of features × number of EMG channels).The dimensionality of the extracted feature set was

reduced using the Spectral Regression (SR) dimensionality reduction method proposed by Cai et al. [43] and also used in [44]. SR maps the original feature set into a new domain with $c-1$ features only, with c being the number of classes, i.e., 5 features in our problem.

In order to perform the classification of the reduced sets of features extracted in the previous step and to check the robustness of the proposed features to diverse classification schemes, four different classifiers were utilized in the experiments: Linear Discriminant Analysis (LDA) [13], [45], Naive Bayes (NB) [46], Random Forest (RF) [47], and k-Nearest Neighbour classifier (kNN) with k= 3 [18]. Majority Voting (MV) was not used in the post-processing of the classifications since it causes additional delays [39].

E. Impact of the Signal Processing and Training Strategies on the Performance of PR-based EMG Control under Changes in Force Level.

We hypothesise that training data should be acquired from multiple forces to improve the robustness of the PR-based control against changes in force levels. In this section, we describe diverse experimental schemes set up to test this hypothesis. We will also determine the best force levels from which the training data should be acquired if considering only one level of contraction. The three experimental schemes are:

1) Training the classifier with a single force level and testing it with the same level of force(Experimental Scheme 1, often used in the literature in studies disregarding the effect of force variations).
2) Training the classifier with a single force level and testing it with the untrained (unseen) two force levels (Experimental Scheme 2).
3) Training the classifier with all 3 levels of force and testing it with a single level of force at a time (Experimental Scheme 3).

In our first investigation, three trials for each movement are used for training and the rest of the trials are used for testing (two to five trials).

F. Statistical Tests

Finally, in order to validate the statistical significance of the achieved classification results, a Bonferroni corrected Analysis of Variance (ANOVA) test with a significance level of 0.05was utilizedunder the null hypothesis that the classification error rates achieved by TD-PSD and the rest of the feature extraction methods that we compare against are not significantly different from each other. In such a case, small *p*-values of less than 0.05 casts doubt on the null hypothesis and suggest that the performance of each of the different methods being compared is significantly different from each other. As we have multiple factors and factor levels to test against, then a repeated measures ANOVA could be utilized here with factors including the different force levels (3 levels: low, med, and high), different subjects (9 levels: TR1-CG2), and different feature extraction methods (5 levels: including TD-PSD, VD-MOM, AR+RMS, TD, and Wavelets).However, we focus here on analysing the statistical differences between the results achieved by our proposed feature extraction method versus each other method and therefore the resultant *p*-values were corrected with Bonferroni analysis. In this case, for nine amputees each performing various movements at three levels of forces, we have concatenated the results across all subjects and force levels to form larger vectors each of 27 elements (9 subjects x 3 force levels) for each feature extraction method;and ran our Bonferroni corrected ANOVA on that, i.e., comparing our method versus each other method while considering two factors with multiple levels and correcting the output with Bonferroni analysis.

III. RESULTS

A. Impact of the Signal Processing and Training Strategies on the Performance of PR-based EMG Control under Changes in Force Level.

1) Experimental Scheme 1: Training with single force level and testing with the same force level

The average errors of classification for nine amputees are shown in Fig. 5 when training and testing the classifier with the same force (*Experimental Scheme* 1) with five feature sets (Section II. D)and four classifiers. The objective is to examine the effect of force level variation on the performance of PR based EMG control for six classes of movements. The standard deviation across 9 amputees is shown with error bars.

Clearly, it can be seen that the errors for TD-PSD are relatively small for all three forces, as compared to the errors of other FE methods for all classifiers investigated, and they are near the errors for a usable system, hypothesised to be bounded at 10% by Scheme and Englehart [13]. When validating the results with the statistical significance tests, the returned *p*-values indicated significant differences between our proposed feature set and all other feature sets when using the LDA classifier with $p<0.001$ for TD-PSD vs VD-MOM, $p= 0.0029$ for TD-PSD vs. AR+RMS, $p<0.001$ for TD-PSD vs. TD, and $p<0.001$ for TD-PSD vs Wavelet features. The achieved *p*-values with other classifiers also agreed on the superiority of the TD-PSD feature set in this testing scheme with all tests returning *p*-vales< 0.01 (all Bonferroni corrected), thus asserting the statistical significance of the lower classification error rates achieved by our TD-PSD versus all other methods from the literature. Moreover, very little differences among classifiers were observed.

Fig. 5 Average classification errors for nine amputees when training and testing the classifiers with the same force level (Experimental Scheme 1) with five feature sets and four classifiers (LDA, RF, NB and kNN). Standard deviations are shown with error bars.*Ts* denotes testing with a specific force.

2) Experimental Scheme 2: Training with single force level and testing with the untrained (unseen) two force levels.

Fig. 6 displays the average errors of classification for nine transradial amputees to examine the effect of force level variation on the performance of PR based EMG control for six classes of movements. The classifiers are trained at a given force level and tested with the unseen force levels *(Experimental Scheme 2*). The standard deviation across nine participants is shown with error bars. Clearly, the error rates are much higher than when training and testing with the same level of force as shown in Fig. 5.The drastic change in classification accuracy when using a classifier trained with a non-appropriate force (>50%) may occur during the daily life usage of the prosthesis when the amputee may change the force level inadvertently. Thus, it is a very serious practical problem. It may be noticed in Fig. 6 that TD-PSD features outperformed other FE methods, for all classifiers and for all training forces. The results of the statistical tests indicated that there were significant differences between the performance of our proposed feature set and all other feature sets with $p<0.001$ for TD-PSD vs. VD-MOM, $p= 0.0041$ for TD-PSD vs. AR+RMS, $p<0.001$ for TD-PSD vs. TD, and $p=0.0036$ for TD-

PSD vs. Wavelet features. These results clearly indicate the statistical significance of the reduction in classification error rates achieved by our TD-PSD versus all other methods when training with a signal force level and testing with two unseen force levels. An additional important point to note in this training scheme is that training with medium force level and testing with low and high force levels achieved significantly lower, with $p< 0.001$, error rates than when training and testing on the other levels.

Fig. 6 Classification errors of nine amputees when training the classifier with one force and performing the testing with unseen force levels (Experimental Scheme 2). Standard deviation is shown with error bars. *Tr* denotes training with a specific force.

3) Experimental Scheme -3: Training the classifiers with all force levels and testing with single level of force

The results for training the classifiers with the three force levels (low, medium, and high) and testing the classifier with a single level of force at a time (*Experimental Scheme 3*) for nine amputees are shown in Fig. 7. It can be noticed that the error rates dropped significantly from those displayed in Fig.6 for the case of unseen forces. The error rates are approximately 7-18 % when testing with low and medium forces, which is much closer to the acceptable level of error for a usable system[13] than the performance reported in Fig. 6. When training with all forces, TD-PSD features outperformed other FE methods for all classifiers used. The utilized ANOVA test results indicated significant differences with $p<0.001$for TD-PSD vs. VD-MOM, $p<0.001$ for TD-PSD vs. AR+RMS, $p<0.001$ for TD-PSD vs. TD, and $p<0.001$for TD-PSD vs. Wavelet features (all results were corrected with Bonferroni analysis). In Fig. 5, Fig. 6 and Fig. 7, and for all cases, TD-PSD outperformed other FE methods and for all classifiers investigated. This may suggest the suitability of TD-PSD features for a PR system trained with multiple forces based on the analysis of amputees' EMG signals.

Fig. 7 Classification errors for nine amputees when training with all force levels and testing the classifier with each level of the three forces (Experimental Scheme-3). Standard deviation is shown with error bars.*Ts* denotes testing with a specific force.

In order to choose the best classifier to perform the subsequent analysis, we calculated the processing time needed to perform Dimensionality Reduction (DR) and classification for all classifiers for all amputees when we train with all forces on a Pentium-4 computer with an 2.6 GHz Intel Core i5 processor, 8 GB RAM with MATLAB 2013a. Table 2displays the processing time needed to perform the DR and classification for each window of the EMG of length of 150 ms, once the system had been trained, averaged across all FE methods for a given classifier. The table also shows the average classification error for all classifiers. Clearly, it can be noticed that the LDA classifier achieved the lowest processing time and classification error compared to other methods. For that reason, LDA classifier was chosen to perform the subsequent analysis of inter-individual differences in the paper.

Table 2 Average processing time (ms) and average classification error for DR and classification when training with all forces displayed in Fig. 7

Classifier	Average error rates when testing with three forces	Time for DR and classification (ms)
LDA	17.42157894	0.0129
RF	17.96601177	2.04
NB	19.07247126	0.013
kNN	19.13680148	0.784

In order to evaluate the processing time of each window with the different feature sets, we calculated the processing time to perform the FE with LDA classifier when we train with all forces. Table 3shows the processing time calculated in ms for the 5 FE methods investigated in this paper. TD-PSD achieved the fastest processing time of 0.3 ms compared to other FE methods.

Table 3 The processing time (ms)for FE classified with LDA classifier when training with all forces.

Feature set	Time for FE (ms)
TD-PSD	0.2922
VD-MOM	2.2245
AR+RMS	1.9794
TD	0.7887
Wavelet	0.41

A more comprehensive way for experimental Scheme 3 with the results for each amputee with TD-PSD and LDA classifier is shown in Fig.8.For testing with low force, TR1 was the worst performer whereas TR5 was the worst performer when testing with medium and high forces. On the other hand, TR6 was the best performer when testing with medium and high forces while CG1 was the best

performer when testing with low force. Fig.8suggests that the performance for the amputees was variable. Such variability in the results between the subjects may be due to different level of amputation and time since amputation for each amputee[45].

Fig. 9 shows the average confusion matrix for nine amputees with TD-PSD and LDA classifier with experimental scheme 3 when testing with A)low, B) medium and C) high forces. The average classification accuracy when testing with low force was 93% while for medium and high forces; the classification accuracy was 90.3% and 82%, respectively. The data suggest a tendency for errors to occur in the fine pinch and spherical grip in all forces. This will be further discussed in Section IV.

Fig.8 The results the experimental Scheme3 for nine amputees when training with all forces with TD-PSD and LDA classifier for nine amputees. The mean of all amputees is shown and error bars represent standard deviation.

We compared the classification performance of the proposed TD-PSD to the state-of-the-art FE method based on Discrete Fourier Transform (DFT) with 2 normalization schemes (Norm-1 and Norm-2) [29]. Table 4 illustrates the average classification errors with their standard deviation across 9 amputees when training with all forces and testing with a single force level at a time with LDA classifier. We also calculated the processing time to perform FE with DFT method and the proposed TD-PSD for the sake of comparison on a Pentium-4 computer with an 2.6 GHz Intel Core i5 processor, 8 GB RAM with MATLAB 2013a.

Table 4 Average classification errors in percent (and their respective standard deviation) for 9 amputees when training with all forces and testing with each force level for several FE methods available in the literature, including the recently proposed DFT features (LDA classifier was used).

Feature Set	Low	Med	High
TD-PSD	7.70 ± 2.89	9.91 ± 3.91	18.54± 7.37
VD-MOM	17.74 ± 7.35	18.82 ± 5.78	30.82 ± 10.78
AR+RMS	10.71 ± 4.33	12.75 ± 5.00	20.89 ± 7.62
TD-PSD	12.98 ± 8.23	15.54 ± 6.19	27.83 ± 7.86
Wavelet	13.38 ± 7.28	15.95 ± 5.11	27.75 ± 10.31
DFT-Norm-1	25.13 ± 10.68	25.40 ± 7.85	36.95 ± 10.75
DFT-Norm-2	21.26 ± 9.45	22.54 ± 6.23	33.43 ± 8.50

Fig.9 Confusion matrices while training the LDA classifier on the data from all forces and testing the classifier on TD-PSD features extracted from EMG data collected at A. Low force, B. Medium force, C. High force. Results averaged across nine amputees performing six classes of hand movements at each force level and standard deviation is shown. Numbers represent the following:1) Thumb flexion; 2) Index flexion; 3) Fine pinch; 4) Tripod grip; 5) Hook grip (hook or snap); 6) Spherical grip (power).

IV. DISCUSSION

We have explored the important practical problem of developing robust PR-based system for the myoelectric control of hand prostheses in the presence of force variations. This problem is recognized as a major barrier to the widespread use of this kind of prostheses[13]. We investigated the impact of the force variations in the classification performance for a relatively large group of transradial amputees and evaluated the improvements that can be achieved when training with more than one force level. This evaluation comprehensively tested four classifiers and five feature extraction algorithms. In this regard, it must be noted that we also proposed a modified set of features (TD-PSD) that proved practically to be more robust to variations in the force level than other feature extraction methods. This is due to the fact that it is based on the orientation of the EMG power spectrum features rather than the amplitude of the EMG power, which is significantly affected by variations of force levels. When considering the level of classification errors and processing time, our results suggests that a PR system based on TD-PSD features, SR feature reduction and LDA as a classifier might provide a reliable control of hand prostheses with six movements for amputees with eight EMG channels. In the next subsections, we discuss the major contributions of this paper in details.

A. Impact of the Signal Processing and Training Strategies on the Performance of PR-based EMG Control under Changes in Force Level.

Experimental scheme 1 evaluated the performance when training and testing the classifiers with the same force level on a sample size of amputee people larger than previous studies[48]–[50]. As expected, the errors rates were low for all three force levels, as shown in Fig.5.Statistical tests showed that there were significant differences between the performance of TD-PSD and all other features. This is the typical setting used in the literature and this setting can be the missing part of the restrictions faced in real life resulting in the prostheses not having been applied to the real world yet.

The results for the experimental scheme 2, which investigated the real life situation when the force level varies, showed that the error rates >60%, which suggest that the PR system alone, even with a robust feature extraction, may not be enough to solve this problem. Indeed, the high level of errors may make the system unusable. It is worth noting that the performance of TD-PSD was better than that of all FE methods in all the cases investigated. The highest error rates occur when the system was trained with low force and tested with unseen forces (Fig. 6).The experiment was conducted in single-day sessions, and the amputees were not trained well to produce specific muscle patterns at different forces. The performance may be improved by training the amputees for several days to produce many forces for a specific movement**.**

In order to solve the real practical problem illustrated in Fig. 6,we assessed the training strategy of including all force levels in the training set, aiming to reduce the effect of force variation, which was investigated in experimental scheme 3. Ideally, a system must be robust enough so that its performance when training with all forces and testing with different forces would be better than, or at least equal to, the performance that would be obtained when training and testing with forces individually. The results shown in Fig. 7 suggest that this training approach helped to reduce the error rates caused by force variation and bring the errors down to a near usable system (classification error <= 10%) with TD-PSD performing better than all FE methods for testing with the low, medium and high forces, as confirmed by statistical tests. This finding is constituent with the finding of [13] where training with all forces of EMG from intact-limbed subjects helped to reduce the errors to that of a usable system.

In Fig. 7, the error rates for the high forces were much higher than the low and medium forces for all amputees. In general, high force is difficult to perform for an amputee since it requires a lot of effort from them. Additionally, producing a high force level and maintaining it for long time may produce fatigue, since the amputees have not used their stump muscles for long time. This may explain why the error rates were much higher for the high force levels than for the low and medium levels of force, in addition to the changes that the EMG signal undergoes with high force levels[24]. It is worth mentioning that TD-PSD achieved 0.3 ms window processing time which is faster than other methods which suggests its suitability for real time implementations. It may be also seen that the lowest error

was when the system is trained with all forces and tested with low force. This may be helpful in the everyday scenario, since the amputee could use the prosthesis in two modes (the low and moderate force levels).

Fig. 8 displayed the errors for experimental scheme 3 in a more comprehensive way to examine the errors for each individual amputee when training with all forces and testing with single force with TD-PSD and LDA. TR6 was the best performer when testing with medium and high forces while CG1 was the best performer when testing with low force. Moreover, TR7 achieved a relatively good performance compared to other amputees despite his vision problems that restricted his use of the VF.

We found the performance of the 2 congenital amputees (CG1 and CG2) to be similar or comparable to that of traumatic amputees, unlike the findings of [49], [50] where the recruited traumatic transradial amputees had a performance better than the other two congenital amputees. This may be explained by the fact that CG1 and CG2 used a myoelectric prosthesis for around 8 years (Table 1)which emphasises the effect of training on reproducing specific muscle patterns to improve performance.

It can be seen in Fig. 7 that testing with high force was worse than testing with medium force or low force for all amputees. This finding is in agreement with [13], who found that the larger errors were achieved at higher force levels than those achieved in small force levels, based on EMG signals of normal subjects for multiple forces for nine classes of movements with eight electrodes. In this study, a similar finding to that of [13] has been revealed. However, it must be noted that we have verified this for a larger sample of nine amputees than previous articles.

From examining the confusion matrices in Fig.9 (A), fine pinch and spherical grips are the movements with the highest errors. When testing with the medium force Fig.9 (B), the errors were in the aforementioned movements as well as hook grip. As for Fig.9(C), all the movements have an error rates around 20% apart from the thumb and tripod grip. It is worth noting that thumb flexion was one of the movements with low errors in all cases for all amputees which is constituent with the finding of [45].

As illustrated in Table 4, the classification performance of the DFT features was not as good as that of our proposed TD-PSD features. On the other hand, the processing time for DFT was 0.2 ms, which is

slightly faster than the proposed TD-PSD (0.3 ms as shown in Table 3). The performance drop of the DFT on amputee datasets may be explained by the limitation that was acknowledged in [29]. The DFT FE requires specific configuration by which the EMG electrodes should be attached on a specified forearm muscles in order for the algorithm to work. When working with amputees, it is very difficult to locate the muscle locations on the stump. Moreover, He *et al.* investigated only grip and wrist movements, which are controlled by superficial muscles. In our study, we investigated finger, grip and wrist movements. Since thumb and index fingers are controlled by deep muscles in the forearm [45], this make it impossible to reproduce the configuration of He *et al.*[29] on amputee people. Additionally, the DFT method relies mainly on percentage of power or strength of muscles contraction along certain frequency bands in relation to the total power by all muscles, a technique that proved to perform well in terms of classification accuracies when tested on intact-limbed subjects [29]. However, when dealing with amputees, the degree of muscle power coordination between the different muscles may not be the most significant feature as factors like the level of amputation, the time since amputation, the innervation of these muscles and others can all significantly affect the performance of such a method. We hypothesize that this is what happened when we tested the method by He *et al.* on amputees as our results in Table. 4 show. In contrast, our method relies on the orientation of the power features extracted from individual muscles and a reference feature vectors extracted from the same muscles, rather than as a percentage of that the power produced by all other muscles, which in this case proved to be of significant importance to the amputees.

As a final remark, it should also be noted that the experimental protocol of the current study focused on finger and grip movements, whereas He *et al.*[29] focused more on wrist movements. This may explain why DFT performance (the muscle coordination-based method) was not as good as our proposed TD-PSD. It is anticipated that the muscle coordination method in [29] may work well for gross-kind of movements such as wrist movements, rather than the more precise-controlled movements such as finger movements.

B. Limitations and future work

The study has a potential limitation that the analysis of the nine amputees EMG signals was performed offline and the amputees did not use a virtual environment or actuated prosthesis to

perform the PR experiments. Another limitation is that no quantified information of force level was provided to the amputees during experiment. Further analyses are warranted in this research direction to perform real- time experiments with the transradial amputees. In addition, the use of an alternative method of contraction will be investigated by using ramp contractions instead of static contractions to see if they can help to reduce the effect of force variation.

V. CONCLUSION

The practical problem of force level variation with everyday use of the prosthesis was investigated for large number of amputees. Significant improvements of ≈ (6-8) % in the classification performance on average across all subjects and force levels when training with all forces were reported due to the use of TD-PSD features, which outperformed all feature extraction methods for all classifiers. Therefore, a major recommendation of this study is that it is important to take into account the effect of force change on the performance of multi-functional upper-limb prosthesis controlled by the EMG for both congenital and traumatic transradial amputees. This effect is important for non-amputee control subjects and even more for the amputees since many factors are changed after the amputation process, such as the loss of visual feedback and the loss of part of the muscle structure. The proposed feature extraction method achieved low levels of error and fast response time compared to other methods based on testing with EMG signals acquired from large number of amputees. TD-PSD can be a potential candidate to replace the existing FE methods to enable the clinical implementation of PR-based systems for amputees' use. In addition, it is important to train the PR systems for controlling the prostheses with a variety of force levels to ensure a classification robust to the force variation.

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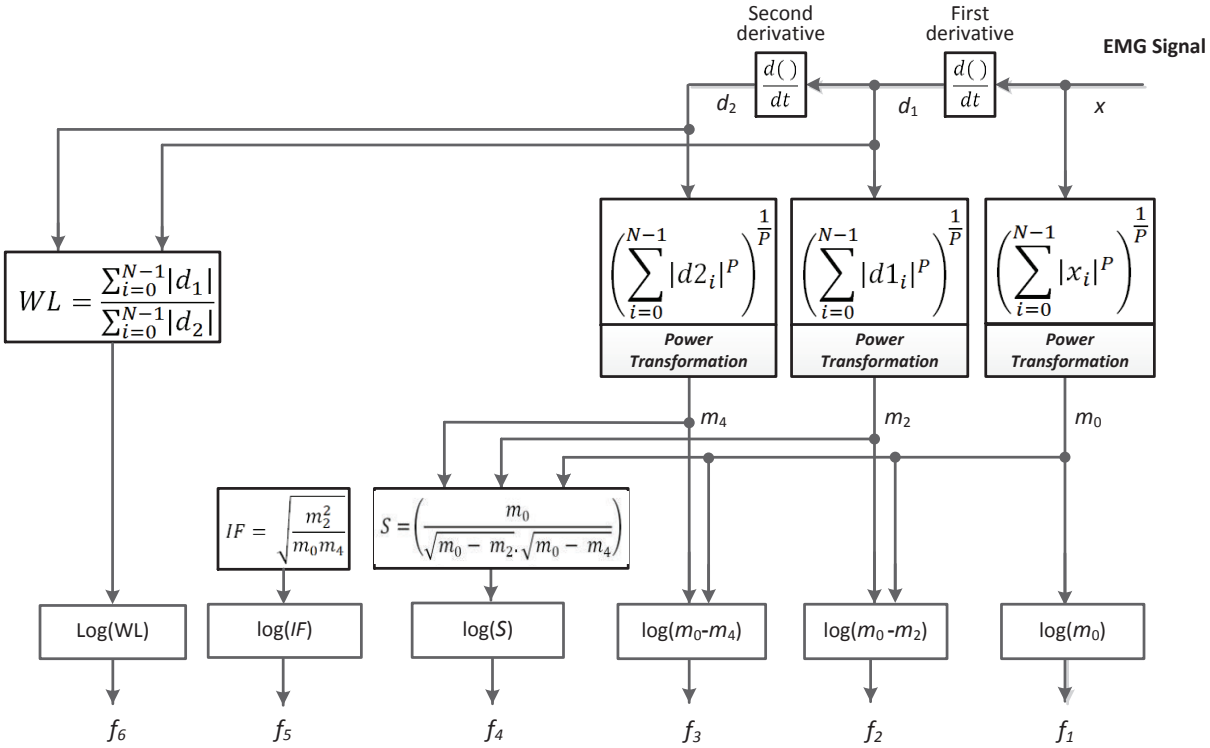
Second derivative
First derivative
EMG Signal
$\frac{d(\,)}{dt}$
d_2
d_1
x
$WL = \frac{\sum_{i=0}^{N-1}|d_1|}{\sum_{i=0}^{N-1}|d_2|}$
$\left(\sum_{i=0}^{N-1}|d2_i|^P\right)^{\frac{1}{P}}$
$\left(\sum_{i=0}^{N-1}|d1_i|^P\right)^{\frac{1}{P}}$
$\left(\sum_{i=0}^{N-1}|x_i|^P\right)^{\frac{1}{P}}$
Power Transformation
Power Transformation
Power Transformation
m_4
m_2
m_0
$IF = \sqrt{\frac{m_2^2}{m_0 m_4}}$
$S = \left(\frac{m_0}{\sqrt{m_0 - m_2}\cdot\sqrt{m_0 - m_4}}\right)$
Log(WL)
log(*IF*)
log(*S*)
log(m_0-m_4)
log(m_0-m_2)
log(m_0)
f_6
f_5
f_4
f_3
f_2
f_1

Fig. 1

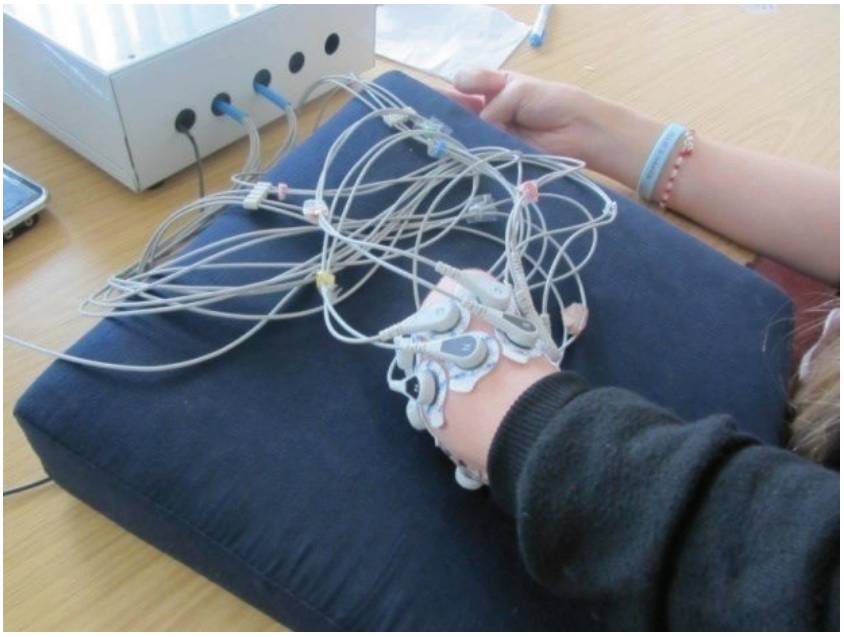

Fig. 2

Fig.3

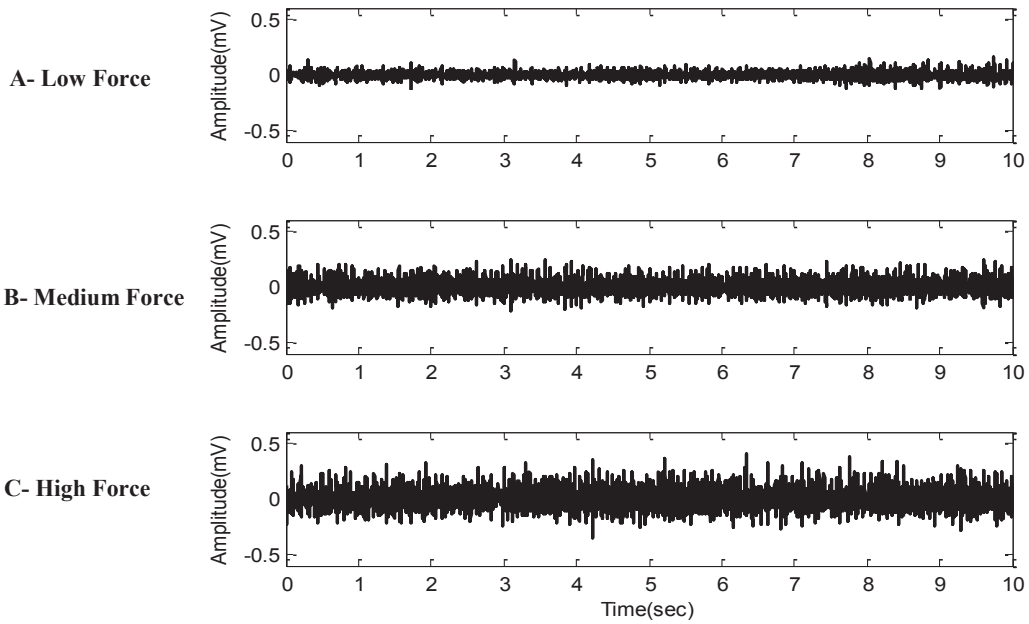
A- Low Force
B- Medium Force
C- High Force
Amplitude(mV)
0.5
0
-0.5
0
1
2
3
4
5
6
7
8
9
10
Time(sec)

Fig.4

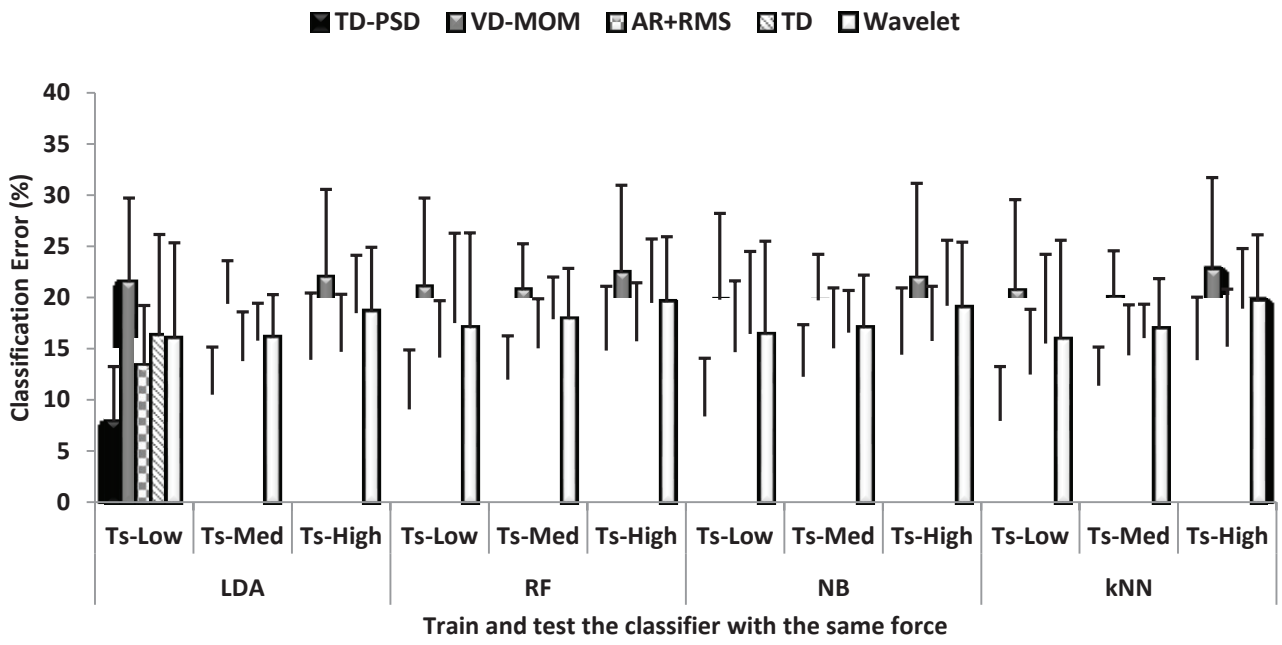
TD-PSD
VD-MOM
AR+RMS
TD
Wavelet
Classification Error (%)
40
35
30
25
20
15
10
5
0
Ts-Low
Ts-Med
Ts-High
LDA
RF
NB
kNN
Train and test the classifier with the same force

Fig. 5

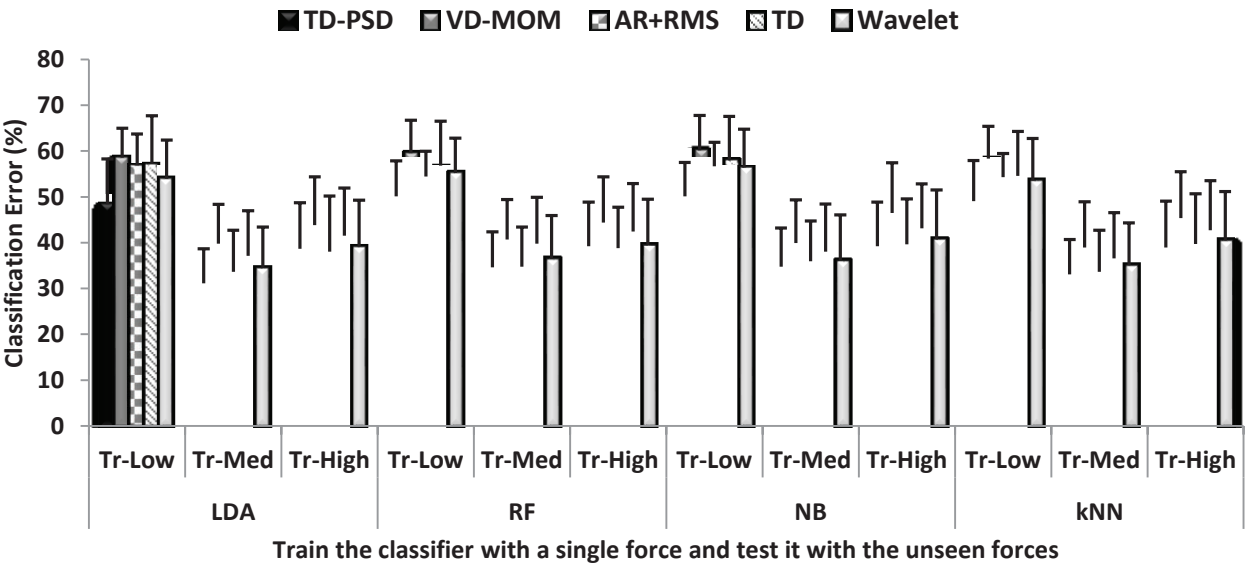
TD-PSD
VD-MOM
AR+RMS
TD
Wavelet
Classification Error (%)
80
70
60
50
40
30
20
10
0
Tr-Low
Tr-Med
Tr-High
LDA
RF
NB
kNN
Train the classifier with a single force and test it with the unseen forces

Fig. 6

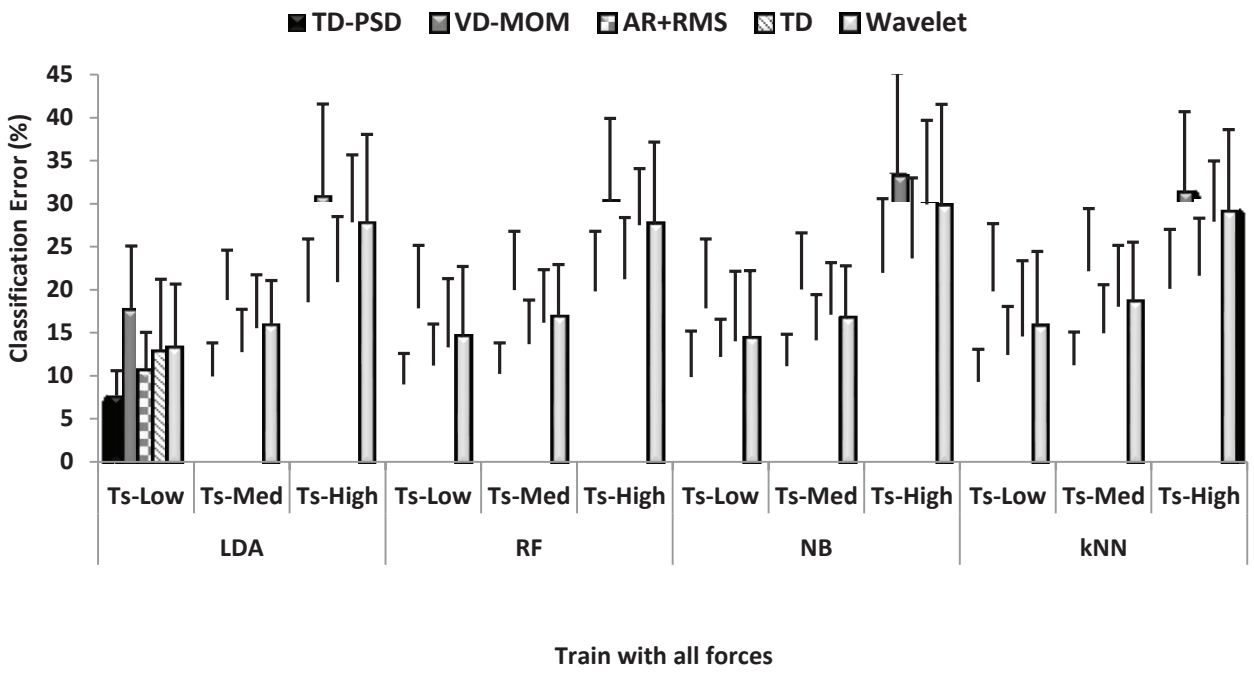
TD-PSD
VD-MOM
AR+RMS
TD
Wavelet
Classification Error (%)
45
40
35
30
25
20
15
10
5
0
Ts-Low
Ts-Med
Ts-High
LDA
RF
NB
kNN
Train with all forces

Fig. 7

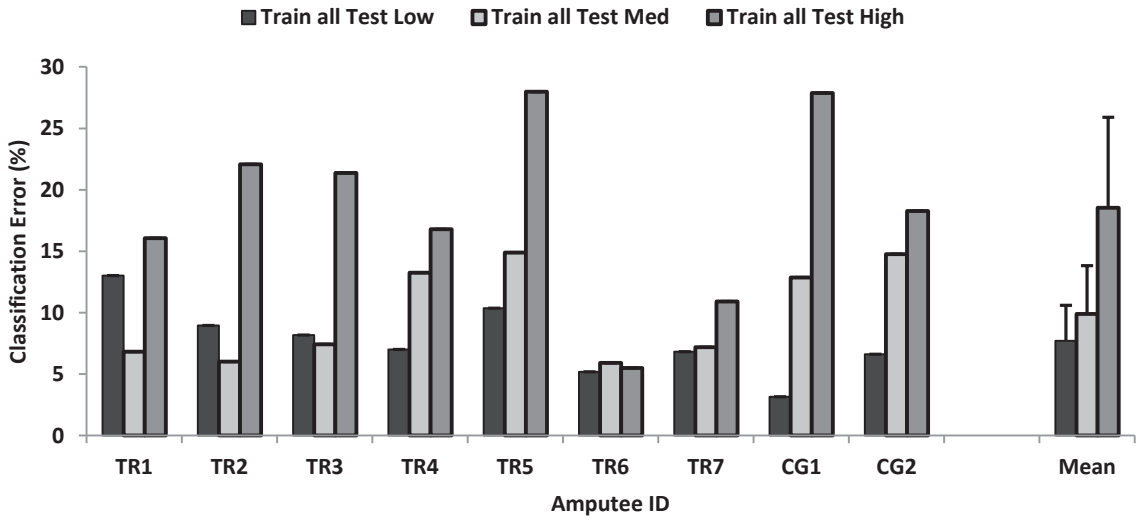
Train all Test Low
Train all Test Med
Train all Test High
Classification Error (%)
30
25
20
15
10
5
0
TR1
TR2
TR3
TR4
TR5
TR6
TR7
CG1
CG2
Mean
Amputee ID

Fig.8

Output Movement

Target Movement	1	2	3	4	5	6
1	99.15% (1.40)	0.57 (0.91)	0 (0)	0.16 (0.44)	0.09 (0.17)	0.03 (0.08)
2	1.44 (3.57)	95.30% (8.85)	2.42 (3.91)	0.72 (1.93)	0.09 (0.15)	0.02 (0.07)
3	0.33 (0.37)	3.38 (3.53)	88.00% (12.85)	7.18 (11.23)	0.20 (0.3)	0.91 (1.61)
4	0.46 (1.34)	0.83 (1.4)	3.49 (7.15)	92.74% (7.45)	2.15 (3.67)	0.33 (0.48)
5	0.02 (0.07)	0.23 (0.41)	0.45 (0.93)	4.79 (8.32)	89.78% (12.96)	4.74 (5.28)
6	0.06 (0.19)	0 (0)	0.39 (0.86)	0.65 (0.81)	5.89 (7.16)	93.01% (6.91)

A. Training with all forces and testing with low force

Output Movement

Target Movement	1	2	3	4	5	6
1	96.70% (3.67)	1.21 (2.56)	0.77 (1.09)	0.93 (1.9)	0.18 (0.33)	0.22 (0.55)
2	1.81 (3.02)	94.01% (4.1)	3.35 (3.42)	0.46 (0.98)	0.26 (0.53)	0.11 (0.19)
3	0.94 (1.81)	2.75 (4.13)	89.34% (14.02)	3.86 (4.39)	2.54 (6.6)	0.57 (0.98)
4	0.21 (0.29)	0.35 (0.38)	3.82 (4.41)	91.60% (5.98)	2.01 (3.65)	2.01 (2.98)
5	0.46 (1.25)	0.11 (0.17)	2.78 (7.52)	3.00 (3.84)	87.55% (13.65)	6.10 (11.57)
6	0.02 (0.06)	0.14 (0.23)	0.49 (0.61)	4.28 (4.94)	12.64 (11.09)	82.43% (11.57)

B. Training with all forces and testing with medium force.

Output Movement

Target Movement	1	2	3	4	5	6
1	98.15 (1.9)	1.14 (1.99)	0.28 (0.38)	0.17 (0.4)	0.23 (0.5)	0.03 (0.1)
2	1.29 (2.29)	80.76 (14.05)	12.03 (12.3)	1.95 (2)	3.51 (5.8)	0.46 (0.7)
3	4.20 (9.97)	3.22 (6.31)	77.36 (22.6)	7.97 (8.2)	4.24 (11)	3.02 (5)
4	0.96 (1.45)	0.17 (0.26)	4.39 (5.28)	81.78 (16)	9.50 (9.5)	3.20 (4.9)
5	0.53 (0.85)	0.70 (1.5)	0.40 (0.44)	5.51 (6.8)	80.37 (15)	12.48 (11)
6	0.75 (1.82)	0.01 (0.04)	4.35 (7.34)	3.11 (4.3)	17.85 (27)	73.93 (24)

C. Training with all forces and testing with high force.

Fig.9