

A Fusion of Time-Domain Descriptors for Improved Myoelectric Hand Control

Rami N. Khushaba¹, Ahmed Al-Ani¹

¹ Faculty of Engineering and IT (FEIT), University of Technology, Sydney (UTS), Australia
Email: Rami.khushaba@uts.edu.au
Ahmed.al-ani@uts.edu.au

Ali Al-Timemy², Adel Al-Jumaily¹

² Biomedical Engineering Department, Al-Khawarzmi College of Engineering, University of Baghdad, Iraq
Email: Ali.althimemy@kecbu.uobaghdad.edu.iq
Email: Adel.al-jumaily@uts.edu.au

Abstract—This paper presents a new feature extraction algorithm for the challenging problem of the classification of myoelectric signals for prostheses control. The algorithm employs the orientation between a set of descriptors of muscular activities and a nonlinearly mapped version of them. It incorporates information about the Electromyogram (EMG) signal power spectrum characteristics derived from each analysis window while correlating that with the descriptors of previous windows for robust activity recognition. The proposed idea can be summarized in the following three steps: 1) extract power spectrum moments from the current analysis window and its nonlinearly scaled version in time-domain through Fourier transform relations, 2) compute the orientation between the two sets of moments, and 3) apply data fusion on the resulting orientation features for the current and previous time windows and use the result as the final feature set. EMG data collected from nine transradial amputees performing six classes of movements with different force levels is used to validate the proposed features. When compared to other well-known EMG feature extraction methods, the proposed features produced an improvement of at least 4%.

Keywords- Electromyogram (EMG); feature extraction; high order derivatives; movement recognition

I. INTRODUCTION

The Electromyogram (EMG) signal plays an important role in many applications [1-2]. In particular, EMG proved to be useful in the identification of repeatable patterns of muscular activities, and hence has been successfully used for task discrimination in the myoelectric control of powered prosthetics for amputees [1-3]. Many research studies have been conducted to enhance the various aspects of myoelectric control, such as signal pre-processing [4], feature extraction [5, 6], channel and feature selection [7], classification and other areas of EMG pattern recognition [8]. Among these various aspects, finding informative features (accurate descriptors) of the EMG signal is of paramount importance, particularly for clinical practice and rehabilitation research [9]. These features need to have the ability to discriminate between the various forearm and wrist/hand gestures/movements, and hence, have direct impact on the success of the EMG pattern recognition systems and their clinical acceptance [10].

Various types of feature extraction methods have been proposed in the literature. These include the mean absolute

value (MAV), waveform length (WL), slope sign changes (SSC), and number of zero crossings (ZC) [11], fast Fourier transform (FFT) [12], wavelets and wavelet packet transform (WPT) [13, 14], cepstral coefficients (CC) [15], Willison amplitude (WAMP) [16], sample entropy (ENT) [17], the autoregressive (AR) model parameters [18], and cardinality [9]. A comparison between 50 feature extraction methods that were developed for EMG pattern recognition is presented in [10]. Despite these attempts, developments of clinically viable systems, particularly those that involve prostheses for amputee use, are noticeably limited [19]. Research in this direction reveals a gap between academia and industry, as there are many challenges that face online EMG pattern recognition. This gap is caused by several factors, such as: lack of intuitive control, poor system reliability and the lack of robustness against practical problems like limb position change, electrodes shift, varying force levels, and signal non-stationarity [20]. Recent studies that attempted to address some of these factors have found that features extracted from the first and second derivatives of the EMG signal could lead to better EMG classification accuracies [21-23], with significant improvements upon several well-known features in problems with changing limb position [21], varying contraction force levels and varying forearm orientations [24].

This paper extends our recent work in this direction [23] by adopting a fusion approach that not only extracts the features from the current analysis windows but, also fuses that with those extracted from previous windows for robust activity recognition. In such a case, the local variability in the EMG features is also correlated to the semi global variability as deduced by the time resolution of the previous windows.

II. METHODS

A. The Proposed Time-Domain Descriptors (TDD)

The block diagram of the TDD features is shown in Fig.1 [23]. The description of the algorithm starts with a sampled version of the EMG signal denoted as $x[j]$, with $j=1,2,...,N$, of length N and a sampling frequency f_s . The EMG trace within a certain epoch can be expressed as a function of frequency X/k by means of Discrete Fourier transform (DFT). The main derivations of the proposed method are based on 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

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

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 [25]. The consequence of this symmetry is that we are left with the option of dealing with the whole spectrum, including positive and negative frequencies, as we have no direct access to the power spectral density from the time-domain. 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 the n^{th} order of the power spectral density $P[k]$, which is given by [25]

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

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

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

To this end, our original time-domain power spectral descriptors (TDPSD) [23] are described below as shown Fig.1.

- **Root squared zero order moment:** indicates the total power in the frequency-domain, or simply the strength of muscle contraction, which is given as

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

- **Root squared fourth and eighth order moments:** according to Hjorth the second moment can be considered as a power, but then of a modified spectrum $k^2 P[k]$, corresponding to a frequency function $kX[k]$. The time equivalent of a k multiplied frequency function is the first derivative of the time function [25]. Thus

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

A repetition of this procedure gives the moment.

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

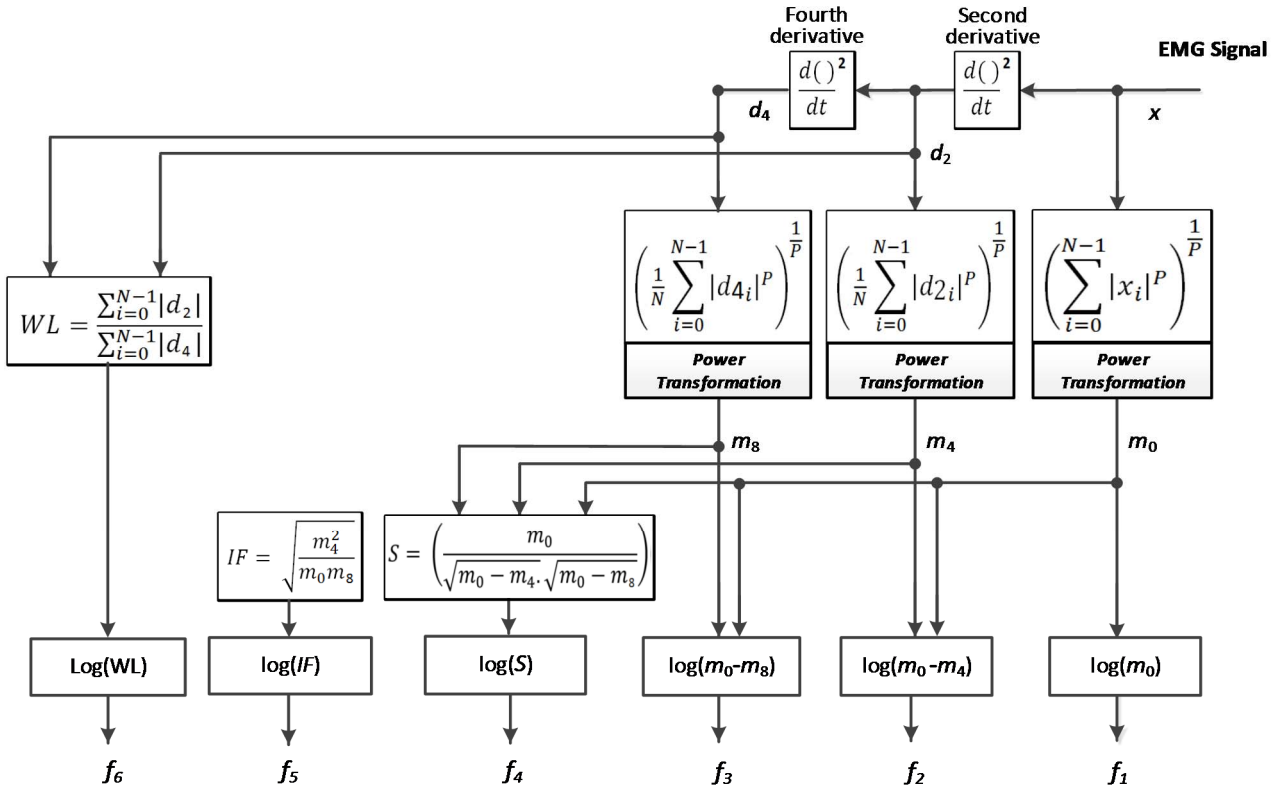


Fig. 1. Block diagram for the derivation of the time-domain descriptors (TDD) feature extraction process, a revised version of that in [23].

Unlike our original work in [23] in which we considered the 2nd and 4th order moment, the first contribution of this paper is an investigation into the utility of the combination of higher order moment, i.e., fourth and eighth order moments. Up to the authors' knowledge, the utilization of high order derivatives into EMG feature extraction is novel as it has not been investigated before. Thus, we define first the 8th order moment as below

$$\bar{m}_8 = \sqrt{\sum_{k=0}^{N-1} k^8 P[k]} = \sqrt{\frac{1}{N} \sum_{j=0}^{N-1} (\Delta^4 x[j])^2} \quad \dots(7)$$

In this case, taking the 4th and 8th derivatives of the signal allows the computation of the spectral moments from the time domain, but it also reduces the total energy of the signal; hence, we apply a power transformation to normalize the range of m_0 , m_4 , and m_8 and to reduce the effect of noise on all moment based features as follows

$$m_0 = \frac{\bar{m}_0^\lambda}{\lambda}, \quad m_4 = \frac{\bar{m}_4^\lambda}{\lambda}, \quad m_8 = \frac{\bar{m}_8^\lambda}{\lambda} \quad \dots(8)$$

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

$$\begin{aligned} f_1 &= \log(m_0) \\ f_2 &= \log(m_0 - m_4) \\ f_3 &= \log(m_0 - m_8) \end{aligned} \quad \dots(9)$$

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

$$f_4 = \log\left(\frac{m_0}{\sqrt{m_0 - m_4} \sqrt{m_0 - m_8}}\right) \quad \dots(10)$$

Such a feature describes a vector with all equal elements with a sparseness measure of zero, i.e., m_4 and $m_8 = 0$ due to differentiation and $\log(m_0 / m_0) = 0$, whereas for all other sparseness levels, it should have a value bigger than zero.

• **Irregularity Factor (IF)**: is defined as a measure that represents the ratio of the number of upward zero crossings divided by the number of peaks. 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 [21]. However, instead of computing the IF feature on the original signal as per our original TDPSD features in [23], we consider a variation of this feature based on m_4 and m_8 . The corresponding feature can be written as

$$f_5 = \log\left(\frac{ZC}{NP}\right) = \log\left(\frac{\sqrt{\frac{m_4}{m_0}}}{\sqrt{\frac{m_8}{m_0}}}\right) = \log\left(\frac{m_4}{m_8}\right) \quad \dots(11)$$

• **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.

$$f_6 = \log\left(\frac{\sum_{j=0}^{N-1} |\Delta^2 x|}{\sum_{j=0}^{N-1} |\Delta^4 x|}\right) \quad \dots(12)$$

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

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: $\mathbf{a}$ (from the EMG record) and $\mathbf{b}$ (from a nonlinearly scaled version of the EMG record), each made up of 6 elements. Our initial features, being a set of 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

$$f_i = \frac{-2 a_i b_i}{a_i^2 + b_i^2}, \quad i = 1, 2, 3, \dots, 6 \quad \dots(13)$$

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), 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. (13). In such a case, feature vector $\mathbf{f}$ is less affected by the level of contraction efforts than $\mathbf{a}$ and $\mathbf{b}$ feature sets, as the resultant vector $\mathbf{f}$ 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 and amputees [12, 23]. In the rest of the paper, we denote feature set $\mathbf{f}$, concatenated from all EMG channels, as the Correlated Time-Domain Descriptors (cTDD).

B. Description of the Proposed Feature Fusion Approach

The second contribution of this paper involves a fusion operation in which the features extracted from the current window are multiplied by the features extracted from the n^{th} previous window. In such a case, if the previous window features are from the same class then the correlation values will be boosted, while for non-similar classes the correlation values will diminish. The block diagram of the complete feature extraction process is given in Fig. 2. In such a process one can also correlates with the 2nd, 3rd, and other windows. Our experiments revealed that instead of correlating with the first previous windows, one can select to correlate with further apart windows, e.g., the 4th previous window is a good option as there may not be any significant accuracy

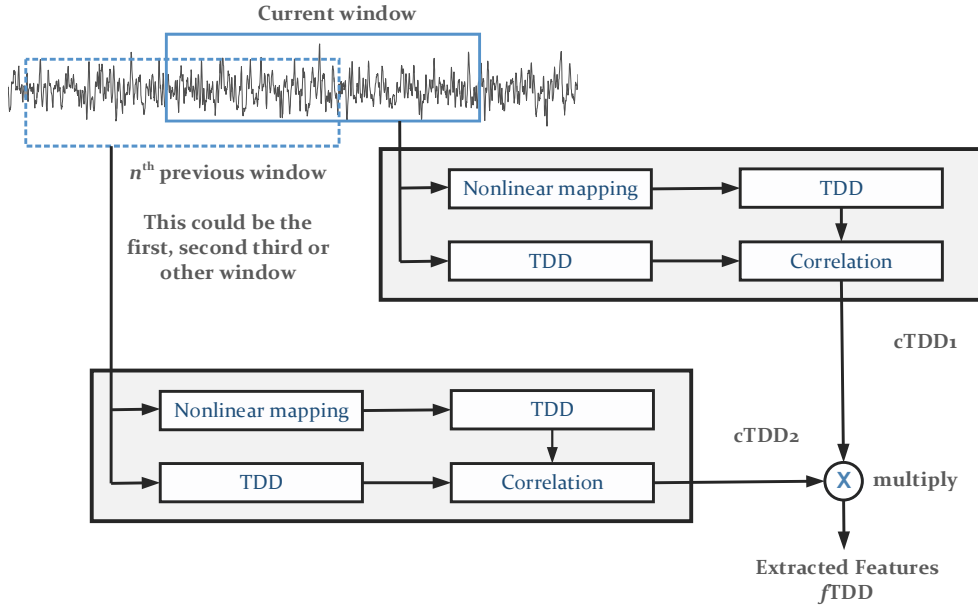


Fig.2 The proposed fusion-based time-domain descriptors (fTDD) feature extraction method.

enhancements after that point (4th previous window selected empirically based on the current data). In the remaining analysis, the result of the two feature sets multiplication process is called the fused TDD or simply **fTDD**.

C. Description of the EMG Data from Amputees

The EMG dataset included data collected from 9 transradial amputees (seven traumatic and two congenital) with unilateral amputation as per earlier description provided in [23]. A custom-build, 8-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 produce the needed force level. The amputees used their intact-hand to help them to imagine the needed movement with the required force.

Six movements including different grip and finger movements were investigated, these movements were: 1) Thumb flexion; 2) Index flexion; 3) Fine pinch; 4) Tripod grip; 5) Hook grip (hook or snap); 6) Spherical grip (power). 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. For each gesture, the amputee produced three force levels: low, med, and high. For each force level, 5 to 8 trials were recorded with each trial lasting for almost 8 to 12sec. Thus, the total number of trials performed by each amputee was equal to the number of movements $\times$ number of force levels $\times$ number of trials for each movement. The EMG datasets for the first 6 amputees TR1-TR6 (Transradial 1 to 6) were collected at the Artificial Limbs and Rehabilitation Centers in Baghdad and Babylon, Iraq, while the EMG datasets for TR7 (Transradial7), 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. 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.3 shows the electrode locations for TR5 as an example.

D. EMG Pattern Recognition Analysis

MATLAB® 2015b 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. To evaluate the performance of the proposed feature set, denoted as **fTDD**, we compare the achieved performance against the performance of some well-known EMG feature extraction methods from the literature, including: a combination of Autoregressive model parameters (5th order) with signal root mean square denoted as **AR-RMS** [27]; the combination of MAV, ZC, SSC, WL denoted as **TD** feature set [11]; the same combination with the WAMP features denoted as **TD1** feature set [28], and the wavelet features extraction method, utilizing the mean of the squared wavelet coefficients at each level as features, with Symmlet family of wavelets and 5 decomposition levels, denoted as **Wavelet**, in addition to our original **TDPSD** feature extraction method based on 2nd and 4th derivatives as in [23].

Finally, in terms of classification accuracy, we have utilized the well-known Linear Discriminant Analysis (LDA) classifier with quadratic function as well as the k-Nearest Neighbour (kNN) classifier, with k=1 chosen empirically. In all analysis, features extracted from the first 3 trials of each hand movement were assigned to the training set, while features extracted from the remaining trials were assigned to the testing set.



Fig.3 Amputee TR5 executing the protocol for recording different force levels. He used visual feedback and the intact limb to produce the spherical grip, as it can be seen in the picture [23].

III. EXPERIMENTS AND RESULTS

The total number of fTDD features for each force level was 48, (number of features (6) $\times$ number of EMG channels (8) = 48). The dimensionality of all of the extracted feature sets was reduced using the Spectral Regression (SR) dimensionality reduction method proposed by Cai et al. [29]. 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 this problem. The classification error rates across all 9 subjects using LDA and kNN classifiers are shown in Fig.4 (a) and (b) respectively, with standard error calculated across all 9 subjects and represented as error bars. In each of these figures, we train the classifiers on the features extracted from each specific force level and test on the features from within the same force level. The results in Fig.4 clearly show that the newly proposed fTDD feature set significantly outperforms other feature extraction methods in terms of classification error rates. The statistical significance was validated by using an N-way analysis of variance test with two factors, the first being the different feature extraction methods, and the second is the different classifiers. At a significance level of 0.05, the achieved p -value reported across the different feature extraction methods was $p < 0.01$ which indicate significant differences between the error rates achieved by the different feature extraction methods. On the other hand, no significant difference between the performance of the different features sets across the different classifiers was observed, i.e., both LDA and kNN performed equivalently. Therefore, in the remaining analysis we stick to LDA only.

In the next part of the analysis, we trained the classifiers based on the features extracted from all force levels and then tested the classifier performance based on features extracted from individual force levels as per the results shown in Fig.5 using the LDA classifier. When validating the results with the statistical significance tests, the returned p -values indicated significant differences between our proposed fTDD feature set

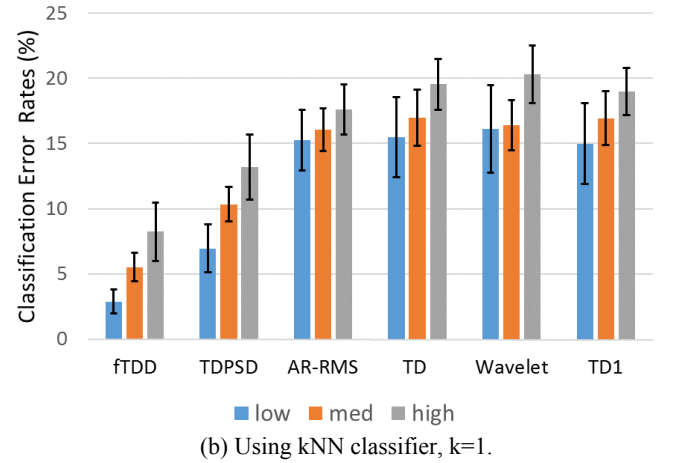
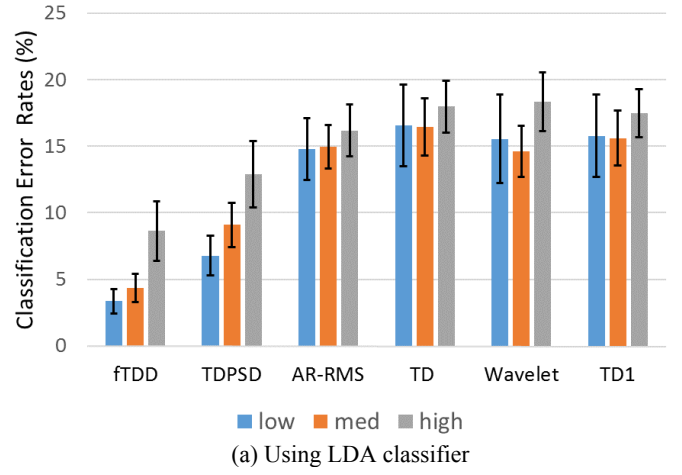


Fig.4 Average classification error rates on all subjects while training and testing on the same force level (error bars represent standard error).

and all other feature sets when using the LDA classifier, with a p -value < 0.01 for all tests.

This in turn further validates the performance of the proposed feature extraction method against all other methods from the literature. In terms of computational efficiency, the time required to extract the fTDD features from 8 channels is on average equivalent to 0.28 ms on a Laptop with 16GB of RAM and i7 processor, which in turn proves the low computational requirements for fTDD, and adds another interesting advantage to the proposed algorithm.

IV. CONCLUSION

A new feature extraction method for EMG pattern recognition was presented based on high order derivatives. The method proposed to extract a set of features that equivalent to the power spectrum moments directly from the time-domain by utilizing Fourier relations and Parseval's theorem. The method included 3 major steps in which a set of features was first extracted from the signal in time-domain, then the same set of features were also extracted from a nonlinearly mapped version of it. In addition, a fusion step was also included in which the extracted features from the current window were multiplied by the features extracted from the previous window. The resulting

algorithm gave significant reductions in classification error rates on EMG datasets collected from amputee subjects. Two classifiers (LDA and kNN) were utilized; however, the obtained results reveal that there were no significant differences between the error rates of these two classifiers. In addition to the above, the extraction of features using the proposed fTDD proved to require significantly low computational cost, which makes it suitable for real-time implementations in any embedded system.

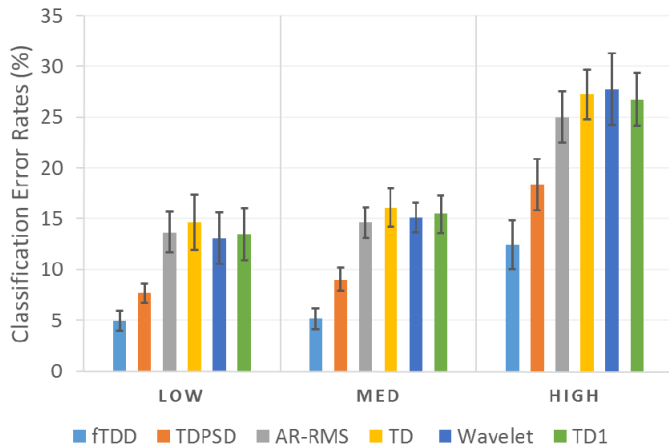


Fig.5 Average classification error rates on all subjects when training the classifier with data from all force levels and testing it with data from individual force levels (error bars represent standard error).

REFERENCES

- [1] G. Rasool, K. Iqbal, N. Bouaynaya, and G. White, "Real-Time Task Discrimination for Myoelectric Control Employing Task-Specific Muscle Synergies," *IEEE Trans Neural Syst Rehabil Eng*, vol. 24, pp. 98-108, Jan 2016.
- [2] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," *J Rehabil Res Dev*, vol. 48, pp. 643-59, 2011.
- [3] D. Farina, N. Jiang, H. Rehbaum, A. Holobar, B. Graimann, H. Dietl, et al., "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges," *IEEE Trans Neural Syst Rehabil Eng*, vol. 22, pp. 797-809, Jul 2014.
- [4] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng*, vol. 50, pp. 848-54, Jul 2003.
- [5] J. Rafiee, M. A. Rafiee, F. Yavari, and M. P. Schoen, "Feature extraction of forearm EMG signals for prosthetics," *Expert Systems with Applications*, vol. 38, pp. 4058-4067, 2011.
- [6] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications*, vol. 39, pp. 7420-7431, 2012.
- [7] R. N. Khushaba, A. Al-Ani, and A. Al-Jumaily, "Orthogonal fuzzy neighborhood discriminant analysis for multifunction myoelectric hand control," *IEEE Trans Biomed Eng*, vol. 57, pp. 1410-9, Jun 2010.
- [8] M. Oskoei, "Myoelectric control systems - A survey," *Biomedical Signal Processing and Control*, vol. 2, pp. 275-294, 2007.
- [9] M. Ortiz-Catalan, "Cardinality as a Highly Descriptive Feature in Myoelectric Pattern Recognition for Decoding Motor Volition," *Frontiers in Neuroscience*, vol. 9, 2015.
- [10] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "EMG feature evaluation for improving myoelectric pattern recognition robustness," *Expert Systems with Applications*, vol. 40, pp. 4832-4840, 2013.
- [11] B. Hudgins, P. Parker, and R. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans Biomed Eng*, vol. 40, 1993.
- [12] J. He, D. Zhang, X. Sheng, S. Li, and X. Zhu, "Invariant Surface EMG Feature Against Varying Contraction Level for Myoelectric Control Based on Muscle Coordination," *IEEE J Biomed Health Inform*, vol. 19, pp. 874-82, May 2015.
- [13] R. N. Khushaba, A. Al-Jumaily, and A. Al-Ani, "Novel feature extraction method based on fuzzy entropy and wavelet packet transform for myoelectric Control," in *Communications and Information Technologies, ISCIT '07. International Symposium on*, 2007, pp. 352-357.
- [14] K. Englehart, B. Hudgins, and P. A. Parker, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng*, vol. 48, pp. 302-11, Mar 2001.
- [15] W. J. Kang, J. R. Shiu, C. K. Cheng, J. S. Lai, H. W. Tsao, and T. S. Kuo, "The application of cepstral coefficients and maximum likelihood method in EMG pattern recognition," *IEEE Trans Biomed Eng*, vol. 42, pp. 777-85, Aug 1995.
- [16] M. Zardoshti-Kermani, B. C. Wheeler, K. Badie, and R. M. Hashemi, "EMG feature evaluation for movement control of upper extremity prostheses," *Rehabilitation Engineering, IEEE Transactions on*, vol. 3, pp. 324-333, 1995.
- [17] X. Zhang and P. Zhou, "Sample entropy analysis of surface EMG for improved muscle activity onset detection against spurious background spikes," *Journal of Electromyography and Kinesiology*, vol. 22, pp. 901-907, 2012.
- [18] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Trans Biomed Eng*, vol. 52, pp. 1801-11, Nov 2005.
- [19] N. Jiang, S. Dosen, K. R. Muller, and D. Farina, "Myoelectric control of artificial limbs- is there a need to change focus?," *IEEE Signal Processing Magazine*, vol. 29, pp. 148-152, 2012.
- [20] R. N. Khushaba, "Correlation analysis of electromyogram signals for multiuser myoelectric interfaces," *IEEE Trans Neural Syst Rehabil Eng*, vol. 22, pp. 745-55, Jul 2014.
- [21] R. N. Khushaba, M. Takruri, J. V. Miro, and S. Kodagoda, "Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features," *Neural Networks*, vol. 55, pp. 42-58, 7/ 2014.
- [22] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "Feature extraction of the first difference of EMG time series for EMG pattern recognition," *Computer Methods and Programs in Biomedicine*, vol. 117, pp. 247-256, 11/ 2014.
- [23] A. Al-Timemy, R. Khushaba, G. Bugmann, and J. Escudero, "Improving the Performance Against Force Variation of EMG Controlled Multifunctional Upper-Limb Prostheses for Transradial Amputees," *IEEE Trans Neural Syst Rehabil Eng*, vol. 24, 6, 650-661, 2016.
- [24] R. N. Khushaba, A. Al-Timemy, and S. Kodagoda, "Influence of multiple dynamic factors on the performance of myoelectric pattern recognition," in *Engineering in Medicine and Biology Society (EMBC), 37th Annual International Conference of the IEEE*, 2015, pp. 1679-1682.
- [25] B. Hjorth, "EEG analysis based on time domain properties," *Electroencephalography and Clinical Neurophysiology*, vol. 29, pp. 306-310, 9/ 1970.
- [26] M. Ortiz-Catalan, R. Brånamark, and B. Håkansson, "BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms," *Source Code for Biology and Medicine*, vol. 8, pp. 1-18, 2013.
- [27] A. Chan and G. Green, "Myoelectric control development toolbox," in *Conference of the Canadian Medical & Biological Engineering Society*, ed. 2007.
- [28] E. Scheme and K. Englehart, "On the robustness of EMG features for pattern recognition based myoelectric control: a multi-dataset comparison," *Conf Proc IEEE Eng Med Biol Soc*, pp. 650-3, 2014.
- [29] D. Cai, X. He, and J. Han, "SRDA: An Efficient Algorithm for Large-Scale Discriminant Analysis," *IEEE Trans. Knowl. Data Eng.*, vol. 20, pp. 1-12, 2008.