Journal of Electromyography and Kinesiology 48 (2019) 152–160

Contents lists available at ScienceDirect

Journal of Electromyography and Kinesiology

journal homepage: www.elsevier.com/locate/jelekin

Dynamic time warping for reducing the effect of force variation on myoelectric control of hand prostheses

Omkar S Powar*, Krishnan Chemmangat

Department of Electrical and Electronics Engineering, National Institute of Technology Karnataka, Surathkal, Mangalore 575025, India

ARTICLE INFO

Keywords:
Electromyography (EMG)
Dynamic Time Warping (DTW)
Pattern Recognition (PR)
Force level variation
Classification

ABSTRACT

Research in pattern recognition (PR) for myoelectric control of the upper limb prostheses has been extensive. However, there has been limited attention to the factors that influence the clinical translation of this technology. A relevant factor of influence in clinical performance of EMG PR-based control of prostheses is the variation in muscle activation level, which modifies the EMG patterns even when the amputee attempts the same movement. To decrease the effect of muscle activation level variations on EMG PR, this work proposes to use dynamic time warping (DTW) and is validated on two databases. The first database, which has data from ten intact-limbed subjects, was used to test the baseline performance of DTW, resulting in an average classification accuracy of more than 90%. The second database comprised data from nine upper limb amputees recorded at three levels of force for six hand grips. The results showed that DTW trained at a single force level achieved an average classification accuracy of $60 \pm 9\%$, $70 \pm 8\%$, and $60 \pm 7\%$ at the low, medium and high force levels respectively across all amputee subjects. The proposed scheme with DTW achieved a significant 10% improvement in classification accuracy when trained at a low force level when compared to the traditional time-dependent power spectrum descriptors (TD-PSD) method.

1. Introduction

The electromyography (EMG) signal plays a significant role in prosthetic control since it can be measured non-invasively from the surface of the skin (Peters et al., 2018; Talebinejad et al., 2009). Identification of the patterns of the EMG signals generated due to the contraction of the muscles is a promising approach to control upper limb prostheses (Al-Timemy et al., 2013). Powered upper limb prostheses use EMG signals as a control signal. Multiple degrees of freedom for the prostheses is achieved utilizing a pattern recognition (PR) method, where the myoelectric controller learns the patterns generated during hand movements in the training phase and gives the necessary movement decision during the testing phase (Parker et al., 2006). Many studies have been carried out in this regard, and high classification accuracy has been achieved (He et al., 2015).

A significant number of studies have been performed on the various stages of EMG PR such as pre-processing, feature extraction, novel feature identification, dimensionality reduction, and classification (Powar et al., 2018; Powar and Chemmangat, 2017). There have been problems during the clinical implementation of the system, even though the previous studies have reported a high classification accuracy of more than 90%. There are various other factors that also affect the performance of the PR system, such as variation in limb position, variation in forearm orientation, variation in electrode position, variation in force level, and change in the characteristics of the EMG signal (Khushaba et al., 2016; Staudenmann et al., 2010). It is becoming crucial to test the PR with these various factors, due to the gap between ideal laboratory conditions and practical application of the myoelectric prostheses (Geng et al., 2012). One of the challenging aspects is the force level changes that can arise due to activities such as lifting heavy objects and handling mechanical tools, which can occasionally happen (Shin et al., 2016). Biologically, most changes in force are due to changes in the effort level. If the PR system is not trained for such scenarios, it misclassifies the pattern and produces the wrong control decisions. Therefore, this study intends to investigate the effect of force level changes on the classification accuracy of the PR at three wrist positions.

Recently there has been significant research dedicated towards the problem of force level variations, as they significantly influence the performance of the myoelectric control (Yang et al., 2016; Al-Timemy et al., 2016; Khushaba et al., 2016). MacIsaac et al. (2001) considered the evaluation of muscle fatigue, given both force level variations and joint angle. They stated that both conduction velocity and the EMG mean frequency, affected the performance of the EMG PR. Tkach et al.

* Corresponding author.
E-mail addresses: omkarpowar1991@gmail.com (O.S. Powar), cmckrishnan@nitk.edu.in (K. Chemmangat).

https://doi.org/10.1016/j.jelekin.2019.07.006
Received 26 December 2018; Received in revised form 7 July 2019; Accepted 10 July 2019

(2010) considered two force level variations in their experiments. They showed that selecting suitable EMG feature combinations was not adequate. Developing effective training strategies for the classifier was suggested for improving the robustness. Scheme and Englehart (2011) demonstrated the impact of force changes on the EMG PR-based control. The subjects varied the force level from 20% to 80% of maximum voluntary contraction. The classifier was trained at the individual force level and tested at all force levels. The classification error ranged between 8% and 19%. He et al. (2015) recommended a feature extraction technique based on muscle coordination and discrete Fourier transform. The classification accuracy improved by 11% for the EMG data gathered from nine instructions of motions with three different force levels. Yang et al. (2017) inspected four distinctive data-collection procedures and calculated their efficiency for getting robust classification, despite dissimilarities presented by unlike muscle variations, dynamic arm movements, and outside interfering forces.

Previous research to overcome the effect of force level variation used sophisticated feature selection methods, which often required a higher degree of computation. The classification methods are of three types: (a) feature-based, (b) sequence distance-based, and (c) model-based. The present work proposes the use of the sequence distance-based classification approach, which does not possess evident features and uses the complete data sequence for the classification. The method has been widely used in handwriting recognition, which inspired the present work (Huang et al., 2010). In a sequence distance-based classification, the similarity between sequences is measured by a distance function, which defines the quality of the classification (Xing et al., 2010). Dynamic time warping (DTW) calculates the similarity between two series using a distance measure and has been used previously for the classification of hand movements (AbdelMaseeh et al., 2016). The major advantage of using the DTW method is a better performance with low computational complexity. In most of the previous works, the performance of the method was evaluated on intact subjects rather than on amputees, and it is not known whether these methods can be generalized to amputees since, after the amputation, the muscle structure may change. Several methods were used to this end to overcome force level variation in the EMG classification including time-dependent power spectrum descriptors (TD-PSD), discrete Fourier transforms (He et al., 2015), time domain feature set (Scheme and Englehart, 2011), reduced spectral moments (Vuskovic and Du, 2005), a combination of time-domain and autoregressive model parameters (Oskoei and Hu, 2007), and wavelet features (Al-Timemy et al., 2016). Previous work involved training from all the force levels, that the subject exerted during testing. However, training at all force levels applies only to intact-limbed subjects. Training must be done at a lower or medium force level, for robust applications in amputees. This is to reduce the training time and more importantly, because research shows that amputees are comfortable training in low or medium force levels, rather than at a high force level (Nazarpour et al., 2013). In recent literature, Khushaba et al. (2016) made a thorough study on the impact of force level variation and used the time-dependent spectral feature extraction method to diminish the effect of muscular contraction levels. The EMG records from six classes of hand actions at three force levels were considered, and the accuracy of up to 91% was attained. The technique achieved better performance than previously used methods. The database only contains data from intact-limbed subjects. Hence, the database from Al-Timemy et al. (2016) is also used in the present study, which has data extracted from nine amputee subjects executing six instructions of motions with three different force levels. The method used by Al-Timemy et al. (2016) to overcome force level variation for amputees was the same as used by Khushaba et al. (2016).

The following schemes are used to test the performance of the DTW method: *Scheme I* wherein the training is done with a part of the data pertaining to a single force level and tested on all possible force levels, and *Scheme II* where both the training and testing data include all three force levels. The work demonstrates the capability of DTW on accurate classification for varying force levels and wrist orientations by deploying these two strategies. DTW has been widely used in speech processing, gesture recognition, and even in pattern recognition of biomedical signals (Mazandarani and Mohebbi, 2018). To the authors' knowledge, the present work is the first study, to involve the use of DTW for force level variation. Training only at a specific force level is considered for amputee subjects, as this is the closest to a practical situation. The main contributions of the present paper are: (1) proposing DTW as an alternative to the existing method for improving the robustness of a PR-based myoelectric system in the presence of force level variation; and (2) demonstrating an improvement in classification accuracy when trained at a low force level with amputees in comparison with the TD-PSD scheme (Khushaba et al., 2016; Al-Timemy et al., 2016), and with a reduced computational time. The results of the present study could help in designing a more robust and viable EMG pattern recognition system for upper limb prostheses.

2. Methodology

Two databases were used to demonstrate the effectiveness of the DTW method. The first database involves the use of EMG signals from non-amputee subjects for six hand motions at three force levels each, carried out at three different wrist orientations. The second database is the amputee database for six hand motions, each at three force levels at a single wrist orientation.

2.1. DATASET I: Intact-limbed subjects

2.1.1. Subjects and data acquisition

In the present work, the database from Khushaba et al. (2016) is utilized. The database enables the comparison of the present work to the state-of-the-art to overcome force level variations. The database of Khushaba et al. (2016) consists of EMG signals recorded from ten able-bodied subjects, who had no previous familiarity with the myoelectric framework. The age group varied between 20 and 30 years with forearm diameter of 26.6 ± 2.4 cm.

The EMG signals were acquired from six sensors (Delsys DE 2.x series EMG sensors). The electrodes (bipolar) used were non-invasive 2-slot adhesive skin interfaces mounted on each of the EMG sensors attached to the skin. A reference electrode (Dermatrode reference electrode) was positioned near the wrist of each subject. The six electrodes were placed at equal distances around the forearm of the subject. Then, the EMG signal was amplified with a gain of 1000 and band pass filtered between 20 and 450 Hz. The data was sampled at 4 kHz using a 12-bit ADC from National Instruments (BNC-2090). The database also contained data from the accelerometers attached to the wrist. However, this has not been included in the present study.

2.1.2. Experimental protocol

The data collection strategy adopted in the work of Khushaba et al. (2016) is briefly described in this section for better clarity. The subjects have to undergo a preparatory session before beginning the test. Six classes of movements were performed: (a) hand close (C1), (b) hand open (C2), (c) wrist extension (C3), (d) wrist flexion (C4), (e) ulnar deviation (C5), and (f) radial deviation (C6). The subjects repeated each of these six hand motions at three different force levels, i.e., low, medium, and high. Fig. 1 shows a time series plot of an individual trial for varying force levels when a hand close movement was performed. The database also contains the data described above for three different forearm orientations (Orientation 1, Orientation 2, and Orientation 3) as shown in Fig. 2. Thus, the total number of trials performed on a subject equals to 162 (3 forearm orientations $\times$ 6 movements $\times$ 3 force levels $\times$ 3 trials/movement). Each trial lasted for 5 s with a 10 s break in between. The raw EMG signals were displayed on the screen to help the subject to generate the movement with the necessary force level.

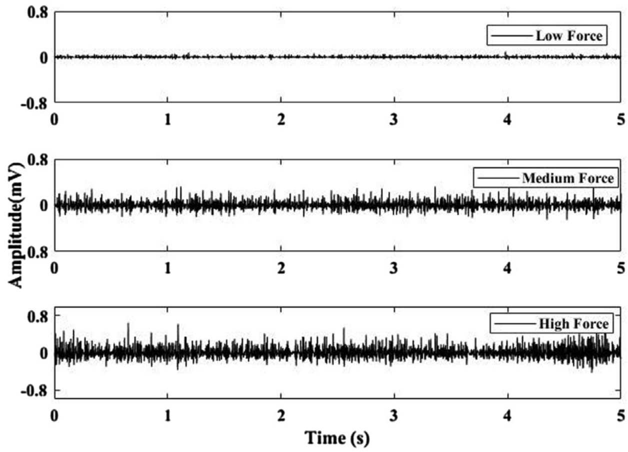


Fig. 1. Three force levels acquired from single channel EMG signal for hand close movement.

2.2. DATASET II: Amputee subjects

2.2.1. Subjects and data acquisition

The second database is taken from Al-Timemy et al. (2016) and consists of EMG signals recorded from nine amputees. The database was collected after getting approval from the local ethical committee. The age group varied between 20 and 57 years, in which the first seven subjects did not use prostheses, and the remaining two used one for a brief duration. A detailed description of the dataset can be found in Al-Timemy et al. (2016).

The Ag/AgCl electrodes (bipolar) (Tyco Healthcare, Germany) connected to a differential amplifier, placed around the left stump, were used to acquire EMG signals from eight channels. The electrode locations can be seen in Al-Timemy et al. (2016). The European recommendations (SENIAM) for the EMG were followed for the placement of the surface electrodes, and to mark the electrode locations, the elbow joint was used as a reference. The channels were connected to differential amplifiers with a gain factor of 1000 per channel and band pass filtered between 20 and 450 Hz. Finally, a custom-built multi-channel EMG acquisition system acquired the signal at a sampling rate of 2 kHz using a 16-bit ADC from National Instruments (USB-6210).

2.2.2. Experimental protocol

Six movements were performed: (a) thumb flexion (P1), (b) index flexion (P2), (c) fine pinch (P3), (d) tripod grip (P4), (e) hook grip (P5), and (f) spherical grip (P6). The amputees were asked to look at the signals on the screen to produce the required force level. They were given time to familiarize themselves with the different force levels. The forces at lower and higher levels than the normal force with which the prosthetic works were recorded. This was simulated since the force level changes during daily life usage. The EMG data was recorded from the amputated hand. The amputees used their intact hand to generate the movement with the required force level. The signal was displayed in LABVIEW (National Instruments) to help the amputees produce the required force level. The amputees produced three force levels (i.e., low, medium, and high) for each of the six movements. Five to eight trials were recorded for each force level (Al-Timemy et al., 2016), for every amputee.

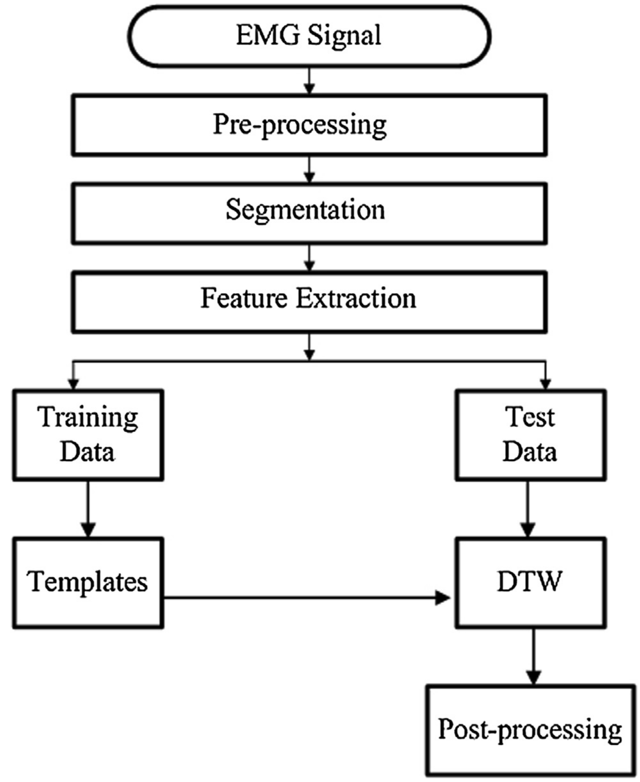


Fig. 3. The overall framework of the suggested PR system.

2.3. System overview

The information flow is shown in Fig. 3. The blocks are explained individually in the following sections.

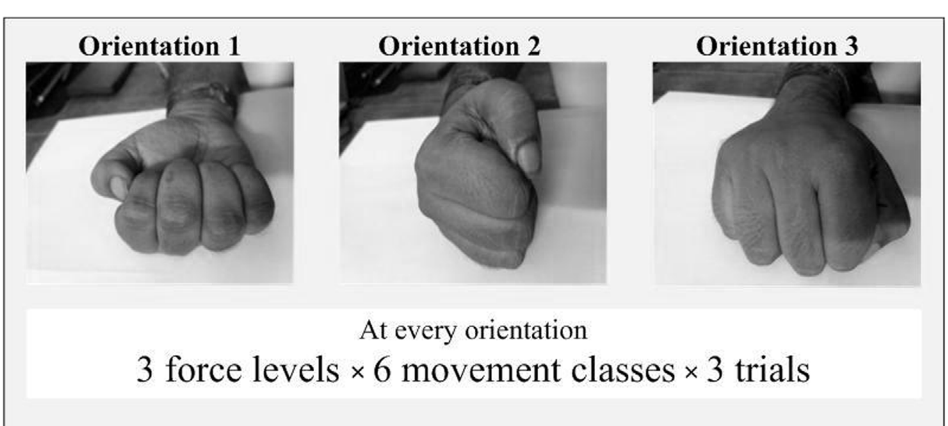


Fig. 2. Data collection at three forearm orientations at three force levels at each movement.

2.3.1. Pre-processing, segmentation, and feature extraction

MATLAB software was used to perform the analysis. The recorded EMG signal was sent to the pre-processing stage, where the noise was removed. The EMG signals were filtered between 20 and 450 Hz using a fourth-order Butterworth filter to eliminate the effect of crosstalk and artifacts caused due to electrode movement. Also, a 50 Hz notch filter was used to remove the power line interference.

Two approaches were tested regarding the data segmentation, mainly to check their suitability for real-time decision-making, one that does not use a windowing scheme and takes the entire 5 s episode during a trial, and the other that uses a disjoint window of size 200 ms. The motivation behind this study is to see the effect of the smaller window size on decision accuracy. The smaller window size also means that the time to make a decision is reduced significantly in real-time.

The well-known root mean square (RMS) value of the signal for a duration of 50 ms was used as the only feature in the present study. The RMS can measure the state of muscle activity, which represents the notable amplitude change of the EMG signal widely used as a feature, and also as a means to reduce the noise in the characterization of the EMG signals.

2.3.2. Dynamic time warping

DTW provides a nonlinear alignment in the two-time series by calculating the distance more wisely. The best alignment between two-time sequence is considered. The two-time sequences are the EMG data; one is the test data, and the other is the template, which is already stored. The users cannot keep their rhythm constant when they perform the same movement (e.g., hand close). The same movement can be performed at different force levels (low, medium, and high). This results in pattern variations and distortions. DTW can be used to improve the performance of PR by permitting the transformation of the time series to identify similar profiles affected by distortion (Huang et al., 2010).

Consider computing the similarity between two arbitrary time series data as shown in Fig. 4. In Fig. 4(b), the Euclidean distance is used to measure the similarity. The Euclidean distance becomes misleading whenever there is a small distortion in the time axis. The distortion due to varying force levels is addressed in this paper. It can observed in Fig. 4(b) that although the two sequences have the same waveform, they are not well aligned in the time axis. Fig. 4(a) represents the two-time series that are dissimilar in the Euclidean distance. DTW algorithm provides a nonlinear mapping resulting in Fig. 4(d) to align them in the time axis. In the Euclidean distance, the two-time series have approximately the same overall waveforms but are not close to each other. DTW warps one-time series nonlinearity to calculate the distance with the other time series more wisely (Fig. 4(c) and (d)).

Consider two EMG signals (training template and test signal) to be compared, A and B of length n, $n \in N$. Let $A =$ {a1, a2, a3,…, an} and B= {b1, b2, b3,…, bn}. DTW aligns A and B by using the following two steps (Senin, 2008; Vial et al., 2009):

Step 1: Distance matrix C is constructed by pair-wise distance between A and B. Consider matrix C with dimension n-by-n, where, the (i_{th}, j_{th}) element of matrix contains the distance d_{ij}.

$$C \in R^{n-by-n}: d_{ij} = \|a_i - b_j\|, i \in [1: n], j \in [1: n] \quad (1)$$

This distance matrix C is called the local cost matrix for the sequence A and B.

Step 2: After the local cost matrix is constructed, a warping path that defines the mapping between A and B is found. Let W represents the warping path. The k_{th} element of W is defined as $w_k = (i, j)$. Therefore, we have:

$$W = w_1, w_2, w_3 \ldots, w_k \ldots, w_K, \qquad n \leqslant K \leqslant 2n - 1 \quad (2)$$

The warping path W must satisfy the following criteria: (1) boundary condition: $w_1 = (1, 1)$ and $w_K = (n, n)$. The starting and ending point of the warping path must be diagonally opposite to the cost matrix; (2) monotonicity condition: Given $w_k = (i, j)$, then $w_{k-1} = (i', j')$, where, $i - i' \geqslant 0$ and $j - j' \geqslant 0$. This makes the points in W to preserve the time-ordering; and (3) continuity condition: Given $w_k = (i, j)$, then $w_{k-1} = (i', j')$, where, $i - i' \leqslant 1$ and $j - j' \leqslant 1$. This makes the allowable step in the warping path to be restricted to the adjacent cells.

Several warping paths fulfill the above conditions, but the path which minimizes the warping cost is of interest.

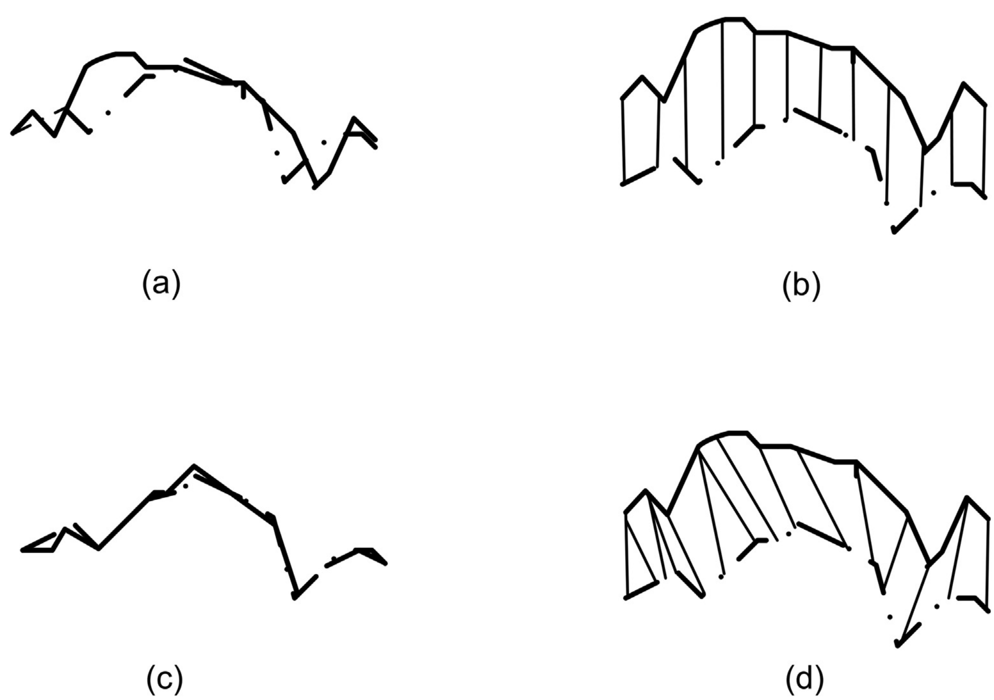


Fig. 4. (a) In Euclidean distance, the two time series are not similar. (b) The waveforms have a similar overall shape; however, they are not well aligned in the time axis. (c) After DTW, a refined distance measure is calculated. (d) Nonlinear alignment is provided by DTW for the two time series.

$$DTW(A, B) = min\left(\sqrt{\sum_{k=1}^{K} w_k}\right) \quad (3)$$

Dynamic warping is used to find the path with minimum cost. The warp path $\lambda(i, j)$ is obtained by sum of the distance $d(i, j)$ found in the current cell and the minimum of the cumulative distances of the adjacent elements.

$$\lambda(i, j) = d(a_i, b_j) + min\{\lambda(i-1, j-1), \lambda(i-1, j), \lambda(i, j-1)\} \quad (4)$$

To sum up, first, the cost matrix is filled one column at a time from the left to the right from the bottom. When the cost matrix is built, a warped path must be found starting from $\lambda(n, n)$ to $\lambda(1, 1)$. The warping path is found by greedy search as described in (4). The smallest warping cost performs the matching of the two signals.

The template here is the training data from the first two trials, and the length of the template is the length of the trials which is the same for all cases. After creating the template, DTW algorithm is applied to the test data to find the matching time points in the template. The distance between the EMG signals for the performed hand movement template and the trained template is calculated. The hand movement is identified with the template of the smallest distance.

The example for hand close (C1) movement recognition is illustrated in Fig. 5. The EMG signals for hand close movement is plotted in the left Fig. 5(a) with all six EMG channels, which match the six forearm muscles. Then, the EMG signal RMS feature is extracted, which is represented as a continuous line in Fig. 5(b). Later, a comparison is made with the six templates, which are the training templates of the DTW as shown in Fig. 5(c). The intended movement is identified using the distance measure calculated by the DTW. The comparison is made on the right side as shown in Fig. 5(c); the template for six hand movements is represented in the dotted line. The calculated distance between the training template and the test template is shown above the plots in Fig. 5(c). The least distance corresponds to the performed hand movements, which is C1 in this example.

The post-processing is done to give this decision to an external prostheses hand from the decision generated using DTW. Classification accuracy is utilized to calculate the hand movement identification performance.

2.4. Data analysis

2.4.1. DATASET I: Intact limbed subjects

The two schemes, as listed in Section 1, are employed for testing the execution of the framework proposed in Fig. 3. The data from two out of the three trials of every subject is used to produce the training set, and the third trial is used for validation of the two schemes. As mentioned in Section 2 (i.e., *2.3.1*), the effect of taking a shorter window on the classification performance is also studied here to check its feasibility for real-time implementation.

2.4.2. DATASET II: Amputee subjects

In the case of an amputee practically using the prostheses, training should be done at a single force level. It is difficult for amputees to train data at a high force level due to fatigue, which may produce tremors on some occasions (Al-Timemy et al., 2016; Nazarpour et al., 2013). Hence, for the amputee database, only training at a single force level is evaluated. In the present study, the first three trials were used for training, and the remainder (two to five trials) were used for testing.

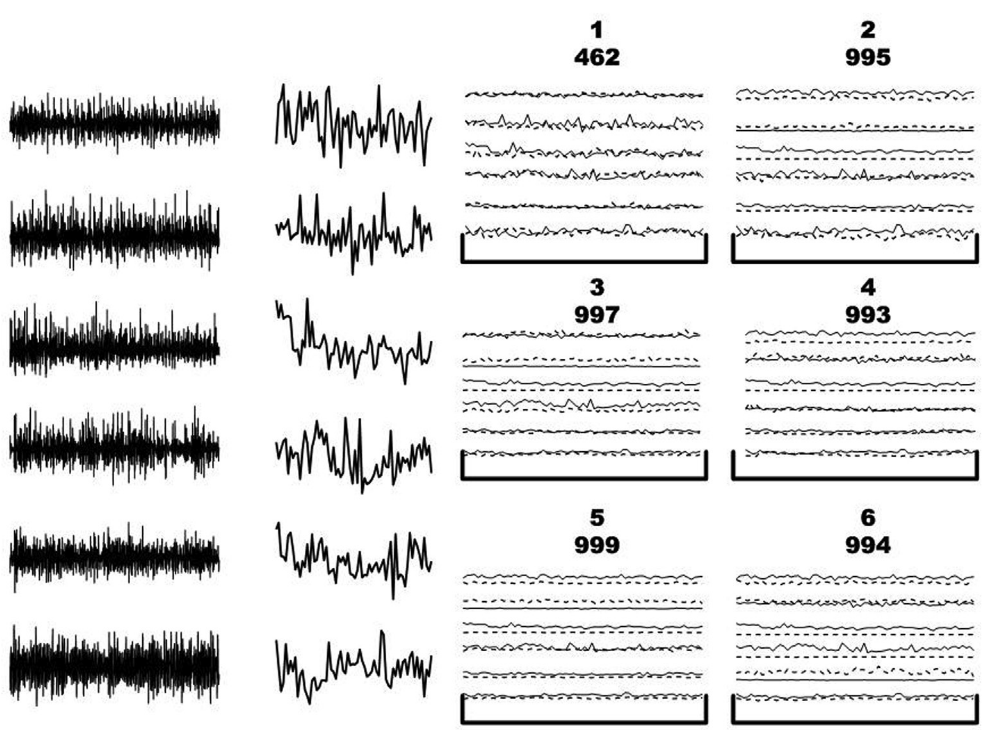
2.5. Statistical test

To test the statistical significance of the achieved results, one-way analysis of variance (ANOVA) was utilized. Also, the well-known two-way ANOVA was used, as multiple factors needed to be tested. An additional significance test known as the t-test was also used. The significance level was set to 0.05 for all the three tests. The *p*-value, along with degrees of freedom (*df*) and *F* values, are reported.

3. Results

3.1. Experiments on DATASET I

In this section, the two training schemes briefly mentioned in



(a) (b) (c)

Fig. 5. An example of hand movement recognition. (a) After filtering, the EMG signal for hand close movement. (b) Feature extraction is done by taking the RMS, represented in continious line. (c) Comparison is done with all the templates (dotted line), the system recognizes the hand movement corresponding to the minimum distance. The x axis represnts the time in seconds which is of 5 s duration. The y axis represnts the (a) amplitude of EMG signal in milliVolts; which ranges between −0.8 mV and +0.8 mV (b) RMS value of the raw EMG signal in (a) which ranges between 0 and 0.15 mV.

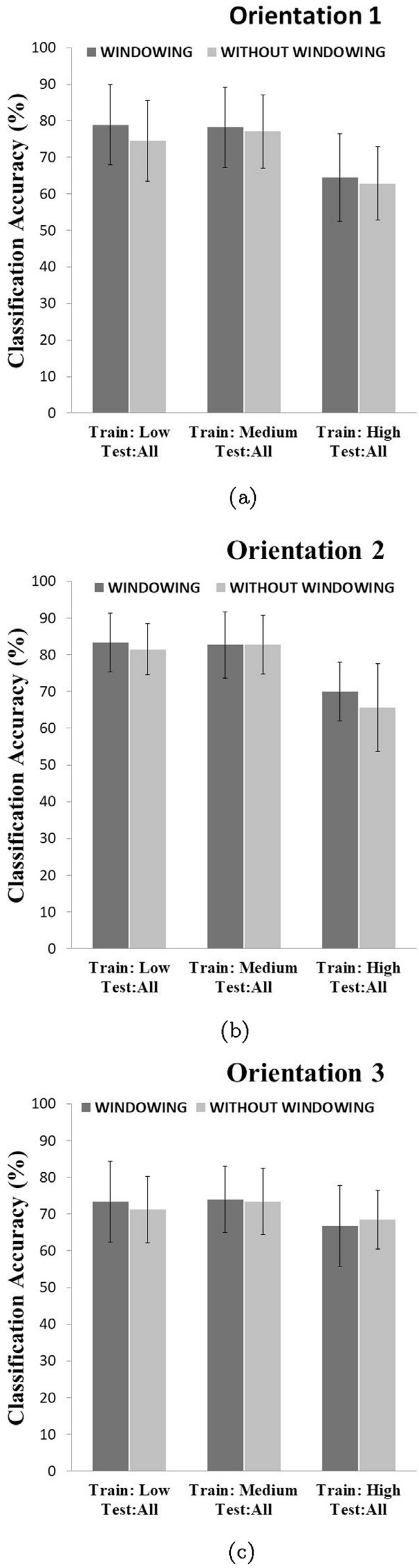


Fig. 6. Average classification accuracy with *Scheme I* obtained across ten subjects for six hand motions at orientation 1 (a), orientation 2 (b) and orientation 3 (c).

Section 1 will be used and their performance with the DTW will be analyzed. The classification accuracy presented is averaged across ten subjects.

3.1.1. Experimental Scheme I: Training the DTW template on the part of the data pertaining to a single force level and testing on all possible force levels

The average classification accuracies for ten subjects are shown in Fig. 6. Fig. 6 shows the results for all three orientations. The error bars represent the standard deviation across ten subjects. The following observations can be made from Fig. 6: (i) there is a significant impact on the performance of the PR system when the subject executes unseen force levels. One-way ANOVA was applied to validate the statistical significance of the classification scores for the three force levels after DTW, which gave ($p = 0.016,\ F = 4.82$ and $df = 2$) at orientation 1, ($p = 0.0024,\ F = 7.72$ and $df = 2$) at orientation 2, and ($p = 0.27,\ F = 1.38$ and $df = 2$) at orientation 3. There was a significant effect of force level variation on the classification accuracy at orientation 1 and orientation 2, and no significant impact at orientation 3; (ii) the trend is similar across all the ten subjects since the error bar lies within $\pm 10\%$. The two-way ANOVA found no significant difference across the ten subjects ($p = 0.14,\ F = 7$ and $df = 2$), and (iii) the effect of windowing (i.e., taking 200 ms data segments) is not significant on the performance of the PR system. To see the effect of windowing, the two-way ANOVA has been applied resulting in the following values ($p = 0.88,\ F = 0.13$ and $df = 2$), ($p = 0.74,\ F = 0.29$ and $df = 2$) and ($p = 0.82,\ F = 0.2$ and $df = 2$) at orientations 1, 2 and 3 respectively. There was no significant effect with and without windowing.

The maximum classification accuracy was obtained at forearm orientation 2 when trained at a low force level (83.3%). Lower accuracy was obtained when trained at a high force level.

Fig. 7 shows the average confusion matrix for the ten subjects with experimental *Scheme I* at orientation 2 when training with low force. The average classification accuracy was 83.3%. Low classification accuracies were observed for hand close (C1), hand open (C2), and wrist extension (C4) movements (<90%). This will be discussed further in the next section.

3.1.2. Experimental Scheme II: Training the DTW template with all three levels of force and testing it with all unseen force levels

Fig. 8 shows the average classification accuracy of the PR system. Similar to Fig. 6, the following can be observed: (i) the accuracy is significantly not affected when a shorter window of 200 ms is used and the results are comparable with the case where the entire 5 s data is used as the training and testing template. This has been further verified by conducting a one-way ANOVA. At orientations 1, 2, and 3, the values were ($p = 0.82,\ F = 0.056$ and $df = 1$), ($p = 0.22,\ F = 1.64$ and $df = 1$)

Target Class \ Predicted Class	C1	C2	C3	C4	C5	C6
C1	**60**	10	0	13.3	6.7	10
C2	0	**73.3**	6.7	0	10	10
C3	0	0	**96.7**	0	0	3.3
C4	6.7	3.3	0	**86.7**	3.3	0
C5	0	0	0	0	**96.7**	3.3
C6	0	3.3	3.3	0	3.3	**90**

Fig. 7. Average confusion matrix with *Scheme I* obtained across ten subjects for six hand movements (hand close (C1), hand open (C2), wrist extension (C3), wrist flexion (C4), ulnar deviation (C5), and radial deviation (C6)) at orientation 2.

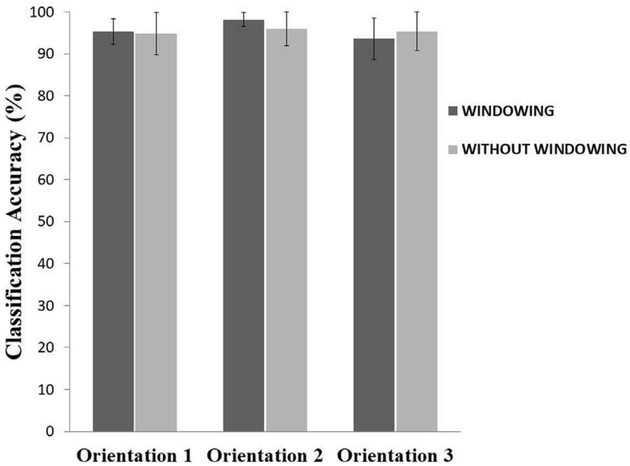


Fig. 8. Average classification accuracy with *Scheme II* obtained across ten subjects for six hand motions from three different orientations.

and ($p = 0.46$, $F = 0.56$ and $df = 1$) respectively. There was no significant effect of windowing; and (ii) the results are consistent across the ten subjects. The one-way ANOVA showed that there is no significant difference across the ten subjects ($p = 0.18$, $F = 1.74$ and $df = 2$). However, it can be seen that, in contrast to *Scheme I* (Fig. 6), the accuracy has improved significantly owing to a wider training set and the results have become much more consistent, with only a ±5% standard deviation. One-way ANOVA conducted on *Scheme I* and *Scheme II* has resulted in the following values: ($p = 0.0003$, $F = 20$ and $df = 1$) at orientation 1, ($p = 0.0002$, $F = 24$ and $df = 1$) at orientation 2 and ($p = 0.0001$, $F = 32$ and $df = 1$) at orientation 3. This indicates that there is a significant change in the classification accuracy in *Scheme II* compared with *Scheme I*.

When deploying *Scheme II*, the average accuracy was always higher than 90%. Specifically, for orientation 2, it was as high as 98.3%, even when using a shorter 200 ms window. This is a significant improvement compared with the earlier reported works in this area.

This indicates the usability of DTW for the PR system trained with all the force levels based on the analysis of the EMG signals. From this, it can be concluded that training should be from all the force levels to increase the robustness of the EMG PR system. This finding agrees with the work of Al-Timemy et al. (2016).

The DTW method was compared with the TD-PSD method by Khushaba et al. (2016). The results of the evaluation are given in Table 1.

The average confusion matrix for the ten subjects with the experimental *Scheme II* at orientation 2 is shown in Fig. 9. From the confusion matrix, it can be observed that the DTW method was successful in classifying the hand motions of all classes with high accuracies (>90%). The movements hand close (C1), hand open (C2), wrist flexion (C4), and ulnar deviation (C5) were classified with 100% accuracy.

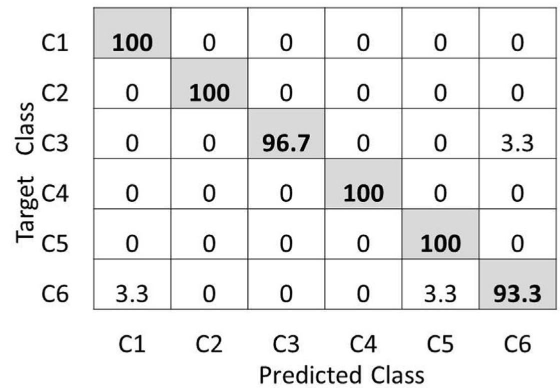


Fig. 9. Average confusion matrix with *Scheme II* obtained across ten subjects for six hand movements (hand close (C1), hand open (C2), wrist extension (C3), wrist flexion (C4), ulnar deviation (C5), and radial deviation (C6)) at orientation 2.

3.2. Experiments on DATASET II

3.2.1. Experimental Scheme I: Training the DTW template on the part of the data pertaining to a single force level and testing on two unseen force levels

To test the generalization ability of the DTW method when implementing the same movement at different force levels, the data from an unseen force level was used for validation. Here, the windowing scheme with a 200 ms window is employed for the validation of the DTW method for the amputee study. The main intention in choosing a 200 ms window is to keep the delay below 300 ms to achieve real-time control. For validating the method, the same scheme as Al-Timemy et al. (2016) was used, in which the training data is acquired from a single force level and the testing data is taken from unseen force levels. Here, the comparison is made with the state-of-the-art TD-PSD method on the same database.

The average classification accuracy for nine amputees using *Scheme I* is shown in Table 2 along with the standard deviation. It can be seen that there is a difference in the accuracy obtained for individual amputees, which may be due to the difference in their amputation level and the time since amputation. As is evident from the table, even though the accuracy is comparable with TD-PSD while training the DTW with medium or high force levels, the proposed method achieved a 10% increase in classification accuracy when trained with a low force level. This was confirmed by the t-test with a p value of 0.03, which indicates that there is a significant difference. This is significant since amputees are comfortable training at lower or medium force levels (Al-Timemy et al., 2016; Nazarpour et al., 2013). Training at a higher force level is difficult for amputees.

The proposed method has been compared with the TD-PSD method on a personal computer with 1.7 GHz Intel Core i5 CPU (4 GB RAM) using MATLAB. The processing time required for a 200 ms rectangular window is shown in Table 2. DTW obtained a lower processing time and classification error when compared with the TD-PSD method.

The following can be inferred from the reported results: Firstly, there is a definite improvement in the classification results when using DTW trained at lower force levels in comparison with TD-PSD. A t-test

Table 1
Comparison of average classification accuracy for TD-PSD method and DTW method for DATASET I.

Method	Classification accuracy %	Reference
Time-dependent power Spectrum descriptors	93	(Khushaba et al., 2016)
Dynamic time warping	98.3	Present study

Table 2
Average classification accuracy (and the standard deviation in %) for nine amputees when trained with single force level and tested with unseen force level for TD-PSD method and DTW method with average processing time.

Method	Low	Medium	High	Processing time (ms)	Rectangular window (ms)
TD-PSD	50 ± 10	70 ± 8	60 ± 10	1.9	200
DTW	60 ± 9	70 ± 8	60 ± 7	1.2	200

was conducted for analyzing the statistical differences between the results achieved using DTW versus TD-PSD. There is a significant improvement in classification accuracy when trained at a lower force level using DTW when compared to TD-PSD ($p = 0.03$). Secondly, the classification accuracy of both DTW and TD-PSD remained the same when trained at medium and higher force levels ($p = 1$). Thirdly, TD-PSD is more expensive in terms of computational cost than the DTW method.

4. Discussion

The main advantage of using the DTW method is that it can overcome the force level variability that affects the classification. Apart from the DTW method, many techniques have been used in the literature, most of them being complex for real-time implementation. In the present study, two datasets were used. In the first database, the performance of the DTW method was validated using two schemes and then compared with the previously used TD-PSD from the literature for non-amputee subjects. Since the database of Khushaba et al. (2016) did not have amputee subject data, the database from Al-Timemy et al. (2016) was used to validate the DTW method for amputee subjects.

4.1. DATASET I: Intact-limbed subjects

The performance of the EMG PR should not vary for various force levels for practical usage. For this, the impact of force level variations on the myoelectric PR system has been studied. Recent literature reports multiple studies to tackle such issues with complex feature selection processes. In contrast, the aim of the present study is to use a simpler and computationally efficient PR system, which can be deployed in real-time without compromising the accuracy. To check the utility of the proposed PR system, the classification accuracy was evaluated on ten individuals performing six hand movements at three different force levels, each at three different hand orientations. The effect of using shorter 200 ms windows on decision-making was also studied. The results indicate that the DTW method is less affected at different force levels and performs well as a PR scheme even when shorter data segments are available for decision-making. This significantly reduces the time to decision, making it a potential candidate for creating a robust, real-time PR system.

4.1.1. Impact of training methods on the performance of PR based myoelectric control under force level variation

In the experimental *Scheme I*, the performance of the DTW method was checked when using the data from one of the three force levels as the training template. The performance was low, as seen in Fig. 6. This finding agrees with the earlier work of Khushaba et al. (2016). Low classification accuracy makes the training strategy adopted in *Scheme I* less suitable for the application. The low classification accuracy attained at individual force levels indicates that more information from other force levels should be included to improve the performance.

Additionally, it was observed that the performance was slightly better when low or medium force was used instead of high force as the training template. This is due to the difficulty in producing a high force level compared with generating low and medium force levels. Maintaining a high force for a substantial amount of time is difficult, and causes fatigue.

An examination of the confusion matrix in Fig. 7, when adopting *Scheme I*, reveals that the classification accuracy associated with the movements hand close (C1), hand open (C2), and wrist flexion (C4) were poor with respect to the other movements. The movements with lower error rates were wrist extension (C3), ulnar deviation (C5), and radial deviation (C6). The misclassification might be because of the variability of the force level and can be further improved by proper training.

Experimental *Scheme II* was employed to overcome the effect of force level variation, which uses all the three force levels to generate the training template. When adopting *Scheme II*, better performance was expected and is shown in Fig. 8. The result shows a clear improvement in the DTW-based PR system performance when deploying *Scheme II*, obtaining an accuracy of 98.2%. This outcome of using the DTW method trained with all the force levels makes it suitable for real-time application.

The average confusion matrix across the ten subjects was calculated and is shown in Fig. 9 to get a better understanding of the accuracy associated with each movement. It can be seen that four out of the six movements obtained 100% accuracy.

4.2. DATASET II: Amputee subjects

The performance of the DTW method is studied under varying force level conditions and is found to be suitable for robust application. DTW has been used before for EMG hand movement classification. However, to the authors' knowledge, the DTW method has never previously been investigated under force level variation on both intact and amputee subjects.

Force variation is one of the major obstacles for the practical implementation of prostheses. The first database, which has data from ten intact-limbed subjects, was used to test the baseline performance of DTW under varying effort levels. The algorithm is further tested on amputee subjects. It performed better than the recently used TD-PSD method in terms of both accuracy and processing time. When considering training at a single force level for amputees, the results suggest that the DTW method provides a more dependable means of control than TD-PSD.

In the TD-PSD method, the error rates for lower force are much higher than the medium and high force levels. However, training an amputee at low and medium force level is relatively easy when compared with a high force level, since training at a higher force level requires a lot of effort and produces tremors in some cases (Al-Timemy et al., 2016; Nazarpour et al., 2013). This explains the importance of training at low and medium force levels rather than a high force level. With the suggested DTW method, as in Table 2, a 10% increase in classification accuracy was obtained when compared with the TD-PSD method with additional savings in computational cost making it an interesting alternative to the previously used PR schemes.

4.3. Limitations and future work

The study has been conducted on databases, and the analysis has been carried out offline. This was to check the utility of the proposed scheme on the performance of the PR system. Future research will study subjects with real-time implementation results. The present method is, however, suitable mainly for a limited set of movements, since adding more movements means more training templates and an increase in the evaluation time. However, this might not be a significant setback for using DTW since the inclusion of further movements has previously been reported to cause fatigue in amputees (Al-Timemy et al., 2016; Nazarpour et al., 2013). As future work, the possibility of incorporating additional sensor data (say hand acceleration) as a surrogate for the EMG sensor data will be investigated to bring down the cost of such systems.

5. Conclusion

The investigation of force level variation was carried out for ten intact-limbed subjects at three force levels with three different forearm orientations. A significant outcome of the study was that DTW, when trained with all force levels can be used as an effective method for the practical implementation of the PR system with faster response time and with simpler computational complexity. A maximum classification accuracy of 98.3% was observed on the available data when DTW method was trained at all force levels. In agreement with what is reported in the literature, it was observed that the performance deteriorated when data from only one of the force levels was used for training.

It was seen that DTW reduces the processing time compared with TD-PSD and has higher accuracy. Also, when testing on the amputee database, DTW managed to outperform TD-PSD in terms of classification performance, with a 10% increase of accuracy when trained at a lower force. This can be considered as a significant contribution of the present research work, and it recommends DTW as a potential tool for prostheses application owing to its pattern recognition capability at lower computational expense.

Declaration of Competing Interest

None.

Acknowledgment

The Visvesvaraya Ph.D. Scheme for Electronics & IT, Government of India supported this work.

References

AbdelMaseeh, M., Chen, T.W., Stashuk, D., 2016. Extraction and classification of multichannel electromyographic activation trajectories for hand movement recognition. IEEE Trans. Neural Syst. Rehabil. Eng 24, 662–673.
Al-Timemy, A.H., Bugmann, G., Escudero, J., Outram, N., 2013. A preliminary investigation of the effect of force variation for myoelectric control of hand prosthesis. In: Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE. IEEE, pp. 5758–5761.
Al-Timemy, A.H., Khushaba, R.N., Bugmann, G., Escudero, J., 2016. Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees. IEEE Trans. Neural Syst. Rehabil. Eng 24, 650–661.
Geng, Y., Zhou, P., Li, G., 2012. Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees. J. Neuroeng. Rehabil. 9, 74.
He, J., Zhang, D., Sheng, X., Li, S., Zhu, X., 2015. Invariant surface EMG feature against varying contraction level for myoelectric control based on muscle coordination. IEEE J. Biomed. Health Inform. 19, 874–882.
Huang, G., Zhang, D., Zheng, X., Zhu, X., 2010. An EMG-based handwriting recognition through dynamic time warping. In: Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. IEEE, pp. 4902–4905.
Khushaba, R.N., Al-Timemy, A., Kodagoda, S., Nazarpour, K., 2016. Combined influence of forearm orientation and muscular contraction on EMG pattern recognition. Exp. Syst. Appl. 61, 154–161.
MacIsaac, D., Parker, P., Scott, R., Englehart, K., Duffley, C., 2001. Influences of dynamic factors on myoelectric parameters. IEEE Eng. Med. Biol. Mag. 20, 82–89.
Mazandarani, F.N., Mohebbi, M., 2018. Wide complex tachycardia discrimination using dynamic time warping of ecg beats. Comput. Meth. Programs Biomed.
Nazarpour, K., Al-Timemy, A.H., Bugmann, G., Jackson, A., 2013. A note on the probability distribution function of the surface electromyogram signal. Brain Res. Bull. 90, 88–91.
Oskoei, M.A., Hu, H., 2007. Myoelectric control systems-a survey. Biomed. Signal Process. Control 2, 275–294.
Parker, P., Englehart, K., Hudgins, B., 2006. Myoelectric signal processing for control of powered limb prostheses. J. Electromyogr. Kinesiol. 16, 541–548.
Peters, K.M., Kelly, V.E., Chang, T., Weismann, M.C., McCoy, S.W., Steele, K.M., 2018. Muscle recruitment and coordination during upper-extremity functional tests. J. Electromyogr. Kinesiol. 38, 143–150.
Powar, O.S., Chemmangat, K., 2017. Feature selection for myoelectric pattern recognition using two channel surface electromyography signals. In: Region 10 Conference, TENCON 2017–2017 IEEE. IEEE, pp. 1022–1026.
Powar, O.S., Chemmangat, K., Figarado, S., 2018. A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals. Biomed. Signal Process. Control 42, 277–286.
Scheme, E., Englehart, K., 2011. Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use. J. Rehabil. Res. Dev. 48.
Senin, P., 2008. Dynamic time warping algorithm review. Inform. Comput. Sci. Department University Hawaii Manoa Honolulu, USA 855, 1–23.
Shin, S., Tafreshi, R., Langari, R., 2016. Robustness of using dynamic motions and template matching to the limb position effect in myoelectric classification. J. Dyn. Syst. Meas. Control 138, 111009.
Staudenmann, D., Roeleveld, K., Stegeman, D.F., Van Dieën, J.H., 2010. Methodological aspects of SEMG recordings for force estimation – a tutorial and review. J. Electromyogr. Kinesiol. 20, 375–387.
Talebinejad, M., Chan, A.D., Miri, A., Dansereau, R.M., 2009. Fractal analysis of surface electromyography signals: a novel power spectrum-based method. J. Electromyogr. Kinesiol. 19, 840–850.
Tkach, D., Huang, H., Kuiken, T.A., 2010. Study of stability of time-domain features for electromyographic pattern recognition. J. Neuroeng. Rehabil. 7, 21.
Vial, J., Noçairi, H., Sassiat, P., Mallipatu, S., Cognon, G., Thiébaut, D., Teillet, B., Rutledge, D.N., 2009. Combination of dynamic time warping and multivariate analysis for the comparison of comprehensive two-dimensional gas chromatograms: application to plant extracts. J. Chromatogr. A 1216, 2866–2872.
Vuskovic, M., Du, S., 2005. Spectral moments for feature extraction from temporal signals. Int. J. Inform. Technol. 11, 112–122.
Xing, Z., Pei, J., Keogh, E., 2010. A brief survey on sequence classification. ACM Sigkdd Explor. Newsl. 12, 40–48.
Yang, D., Yang, W., Huang, Q., Liu, H., 2017. Classification of multiple finger motions during dynamic upper limb movements. IEEE J. Biomed. Health Inform. 21, 134–141.
Yang, Z., Chen, Y., Tang, Z., Wang, J., 2016. Surface EMG based handgrip force predictions using gene expression programming. Neurocomputing 207, 568–579.

Omkar S. Powar is currently working toward the Ph.D degree with the Department of Electrical and Electronics Engineering, National Institute of Technology, Karnataka, India. His research interests include Signal processing and Machine learning techniques for bio-signal characterization.

Krishnan Chemmangat was born in Kerala, India, on December 28, 1984. Krishnan received the Bachelor of Technology (B.Tech) degree in Electrical and Electronics engineering from the University of Calicut, Kerala, India in 2006 and the Master of Technology (M.Tech) degree in Control and Automation from the Indian Institute of Technology Delhi, New Delhi, India in 2008. From July 2008 till March 2010 he was working as a senior engineer – Electronic Controls & Software at General Motors Corporation (GMTCI) Bangalore, India where he was involved in model-based development of automotive climate control systems. In April 2010 he joined as a research scholar at the department of Information Technology, Ghent University Belgium. He then received his PhD degree in Electrical Engineering from Ghent University in May 2014. Later that year he started his academic career with Amrita University, Bangalore where he worked as an Assistant professor at the department of Electrical & Electronics Engineering. In June 2015 he moved to National Institute of Technology Karnataka (NITK) Surathkal where he is currently working as an Assistant professor with the department of Electrical and Electronics Engineering. His research interests include Parametric Macromodeling of complex systems, Machine learning techniques for bio-signal characterization, Black-box modeling and System Identification.