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Towards Resolving the Co-existing Impacts of Multiple Dynamic Factors on the Performance of EMG-Pattern Recognition based Prostheses

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Highlights

- This study systematically investigated the co-existing impact of multiple dynamic factors on the performance of EMG pattern recognition system (EMG-PR).
- An invariant time-domain descriptor was proposed to resolve such co-existing impacts with its performance validated
- The proposed method significantly mitigated combined impact of such factors on the performance of the EMG-PR system.
- The outcomes of the study would be potential for improving the clinical robustness of multifunctional myoelectric prostheses.

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Abstract

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Background and Objective: Mobility of subject (MoS) and muscle contraction force variation (MCFV) have been shown to individually degrade the performance of multiple degrees of freedom electromyogram (EMG) pattern recognition (PR) based prostheses control systems. Though these factors (MoS-MCFV) co-exist simultaneously in the practical use the prosthesis, their combined impact on PR-based system has rarely been studied especially in the context of amputees who are the target users of the device.

Methods: To address this problem, this study systematically investigated the co-existing impact of MoS-MCFV on the performance of PR-based movement intent classifier, using EMG recordings acquired from eight participants who performed multiple classes of targeted limb movements across static and non-static scenarios with three distinct muscle contraction force levels. Then, a robust feature extraction method that is invariant to the combined effect of MoS-MCFV, namely, invariant time-domain descriptor (invTDD), is proposed to optimally characterize the multi-class EMG signal patterns in the presence of both factors.

Results: Experimental results consistently showed that the proposed invTDD method could significantly mitigate the co-existing impact of MoS-MCFV on PR-based movement-intent classifier with error reduction in the range of 7.50%~17.97% ($p<0.05$), compared to the commonly applied methods. Further evaluation using 2-dimentional principal component analysis (PCA) technique, revealed that the proposed *invTDD* method has obvious class-separability in the PCA feature space, with a significantly lower standard error (0.91%) compared to the existing methods.

Conclusion: This study offers compelling insight on how to develop accurately robust multiple degrees of the freedom control scheme for multifunctional prostheses that would be clinically viable. Also, the study may spur positive advancement in other application areas of medical robotics that adopts myoelectric control schemes such as the electric wheelchair and human-computer-interaction systems.

Keywords: Pattern recognition; Upper-limb prostheses; Electromyogram (EMG); Muscle contraction force variation; Subject mobility; Maximum Voluntary Contraction (MVC).

1. Introduction

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The loss of upper extremity motor function caused by amputation or neurological disorder greatly restrict individuals from fully exploring their environment during daily life activities [1]. To adequately restore such function particularly in amputees, the use of assistive medical robotic devices known as prostheses powered by biological signals is considered a viable option [2-5]. Meanwhile, surface electromyogram (EMG) signal recorded during muscle contraction is considered to be the most widely adopted source of control signal for prosthetic control due to its rich neural information content [6]. Remarkably, major advances in prosthetic control technologies have been made with pattern recognition (PR) based approaches since they could potentially support multiple degrees of freedom (MDF) functionalities in an intuitive manner [7-11]. Also, with adequate implementation of the PR-based method, an accurately robust control mechanism for MDF prosthetic devices could be seamlessly realized [10-15]. In this regard, incremental research efforts have been made towards developing intelligently robust PR-based method with improved controllability. For instance, COAPT engineering (a company based in Chicago, U.S.A) recently built the first commercially available intuitive PR-based control systems for advanced prosthetic arms [16]. Despite the advancement made by COAPT engineering [16], Open Bionics [17], Ottobock [18], and other prostheses manufacturers in the recent years, the available MDF PR-controlled prostheses are still being challenged by some confounding factors that in reality limit their clinical and commercial success [16-21].

Recent studies have shown that such confounding issues mainly occur due to inevitable alterations in EMG signal characteristics caused by various inevitable physiological and physical factors. These factors include electrode shift during prostheses donning or usage [22-23], muscle fatigue [24], changes in arm position while observing a set of targeted limb movements [13, 25-27], muscle contractions force variation (MCFV) [28-30], and alterations in EMG signal patterns arising from the mobility of subject (MoS) [10, 31], amongst others. In an attempt to address these issues, Scheme et al. conducted a study and reported that MCFV would significantly degrade the performance of PR-controlled prostheses with limb movement intent prediction error of between 32% ~ 44% [33]. Nazarpour et al. further demonstrated that the degradation arising from MCFV could be attributed to modifications in time-frequency characteristics and probability density function of EMG signals associated with the targeted limb movements [34]. They also reported that MCFV may have negative impact on the overall control performance of the prostheses if neglected [34]. In similar manner, the inevitable changes in EMG signal patterns resulting from MoS has been proved to have a considerable impact on the performance of PR-based movement intent predictor, causing a reduction in the overall system performance in the range of 8.98% ~ 11.35% for non-amputee and amputee subjects [10, 31]. In an attempt to examine the impact of multiple factors on the performance of myoelectric PR-based system, Khushaba et al. conducted a study on the joint influence of forearm orientation and muscle contraction force level on the accuracy of myoelectric PR-based system [27]. Subsequently, they proposed a solution to address the issue, and this represents one of the few studies in this direction to date.

Essentially, MoS and MCFV are two factors that co-exist simultaneously in the practical application of MDF prostheses, but their impact on the performance of PR-based limb movement-intent classifier (a core component that determines the controllability of the prostheses) has only been studied in a mutually exclusive context. Meanwhile, their combined effect remains unknown especially for amputees who are the final users of the prostheses. Hence, this constitute a research gap in the field of PR-based system targeted towards upper-limb prostheses control. *Therefore, it is hypothesized that the performance degradation of the available myoelectric PR-based control systems may be subjectively linked with the non-stationarity of the EMG signal patterns caused by the co-existence of MoS and MCFV. Additionally, we hypothesized that, alterations in the signal patterns arising from the combined impact of MoS and MCFV may differently influence the recognition rate of individual targeted limb movement, thus, degrading the overall performance of the PR-based prosthetic control system.*

Towards bridging this research gap, this study systematically investigated the co-existing impact of the two dynamic factors (MoS and MCFV) on the performance of myoelectric pattern recognition system when utilized to decode multiple-classes of targeted limb movements. The investigation was conducted on the bases of experimental protocols that involved the acquisition of surface EMG signals associated with multiple classes of upper-limb movements in four different scenarios using three distinct muscle contraction force levels, obtained from eight participants (including amputees and ablebodied subjects). Subsequently, the sensitivity of the EMG signal patterns to the combined effect of MoS-MCFV in the context of limb movement-intent decoding were examined, and a new feature extraction method that attempted to mitigate the co-existing impact of both dynamic factors is proposed. Moreover, the performance of the proposed feature extraction method in terms of resolving the co-existing effect of MoS-MCFV on myoelectric PR- system was studied in comparison to other notable existing feature extraction methods using various evaluation metrics. In summary, the main contributions of this study are in three folds:

a) The dynamic co-existence of MoS and MCFV on the performance of PR-based system was systematically investigated towards providing consistently accurate and robust control mechanism for MDF prostheses. It should be noted that this issue has rarely been studied to date, to the best of our knowledge.

b) Towards resolving this issue, this study proposed an invariant time-domain descriptor feature method, whose performance was extensively verified using different metrics.

c) The study further examined how the combined impact of MoS-MCFV could differently influence the prediction of individual targeted limb movement, towards providing proper insight on ways to improve the overall control performance of the PR-based control systems.

2. Material and Methods

2.1 Participant information

Considering the aim of the study, a total of eight subjects (all right hand dominated) were recruited for the EMG data collection task which was done based on a systematically designed experimental protocols. Two out of the subjects are transradial amputees whose residual arm length ranges between 71cm ~ 74cm from their shoulder blade downwards while the remaining six subjects are non-amputees, including 4 males and 2 females. Upon proper examination of the subjects, we found that they are healthy and had no trace of neuromuscular disease that may affect the quality of the acquired EMG signals. Afterward, they were informed about the aim of the study and experimental protocol designed for the data collection. A consent form indicating their willingness to participate in the study with issuance of permission for publication of their data was signed by all the

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subjects and the study protocol was approved by the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences' Institutional Review Board.

2.2 Equipment setup

A wireless surface EMG data collection system manufactured by Delsys Inc., Boston, was utilized for the data acquisition task in the study. Prior to the EMG recordings, the area on each participant's skin mapped out for the sensors' placement was cleaned with alcohol pads to eradicate skin oil that might distort the signal quality. For the amputees, eight wireless bipolar EMG-signal sensors were placed on their residual arms' muscles, with 6 of the sensors distributed around the forearm muscles and the remaining two on the extensor/flexor muscles. Meanwhile, **Figure 1a** shows the electrode placement on the residual arm muscles of an amputee. Note that the orientation and positioning of the sensors were followed by a preliminary assessment of the stump muscles' characteristics especially in the amputees to locate potential sites on the forearm [35]. Seven classes of forearm movements including: hand close and open (HC and HO), wrist flexion and extension (WF and WE), wrist supination and pronation (WS and WP), and no-movement (NM), were designed for the study and the sequence/duration for which each targeted limb movement was performed is shown in **Figure 1b,** using wrist flexion (WF) as the representative limb movement. Meanwhile, the targeted limb movement in this case (WF) is performed five times and each represents a trial, thus resulting in T1, T2, T3, T4, and T5, as shown in **Figure 1b**, with a rest session of about 5 seconds (light gray region) introduced between consecutive trials.

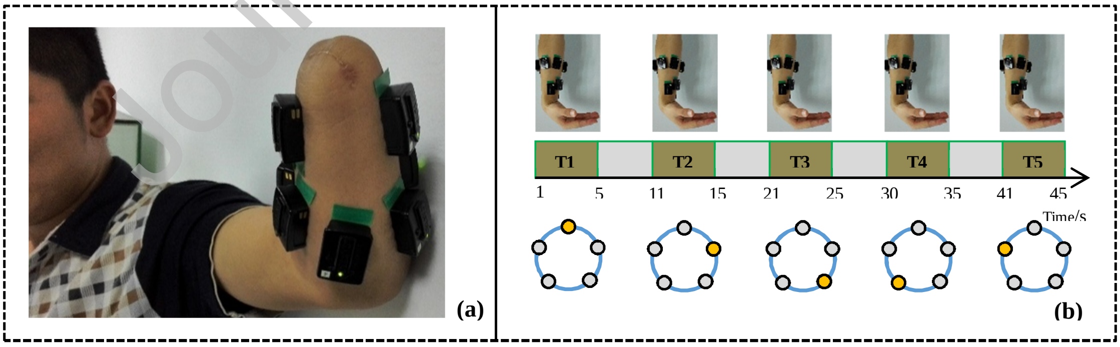

Figure 1: Experiment setup showing electrode placement/configuration on the residual arm muscles of an amputee (a), the sequence and duration for performing each targeted limb movement tasks (b).

2.3 Experimental procedure and Data acquisition

Towards investigating the co-existing impact of MoS-MCFV on the characterization of multi-class EMG signal patterns with respect to PR-based movement-intent classification, experiments that involved the acquisition of EMG data for the above-described classes of targeted limb movements was designed. Considering the first dynamic factor MoS, the subjects were instructed to perform the seven classes of targeted limb movements while they assume four different scenarios including a static scenario (sitting: S1) and three non-static scenarios (S2: ground level walking: S3: ascending a stair, and S4: descending a stair). Meanwhile, they were required to perform the limb movement tasks in each scenario using three different muscle contraction levels (20%, 50%, and 80% MVCs: Maximum Voluntary Contractions), that is varying the second dynamic factor of MCFV. To ensure benchmark experimental procedure, the specified MCFV were designed in line with recommendations from previous studies [28-30, 32-34], and further detail is provided as follows.

a) Low muscle contraction force: In this session, participants are required to utilize 20% MVC force to complete the target limb movements at a time. To ensure that the exerted force corresponds to the expected MVC level, a visual feedback scheme that reflects the muscle contraction level as a function of the amplitude of the EMG recordings was provided. During the pre-experiment sessions, the reports obtained from the participants indicated that the visual feedback scheme was helpful in aiding them to modulate their arm muscles in line with 20% MVC while observing the limb movement tasks.

b) Medium muscle contraction force: In this session, the participants were aided to perform each class of limb movement utilizing a medium muscle contraction force of approximately 50% MVC, which is relatively higher than the low muscle contraction force level. It is noteworthy that visual feedback scheme also aided participants to activate their muscles with the required medium level of force while observing their movements.

c) High force level: In this session, each participant is required to complete a specified forearm movement with a muscle contraction force greater than the medium muscle contraction force. To be precise, with the help of the feedback scheme, the subjects were able to modulate their arm muscle with about 80% MVC while performing the tasks. Meanwhile, the participants were trained on contracting their muscles with a high force

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that is comfortable to avoid attaining the MVC since it may cause muscle fatigue especially for amputees whose residual arm muscles have not been put to use for a long time. Figure 2 shows the conceptualized framework with which the experiments were conducted.

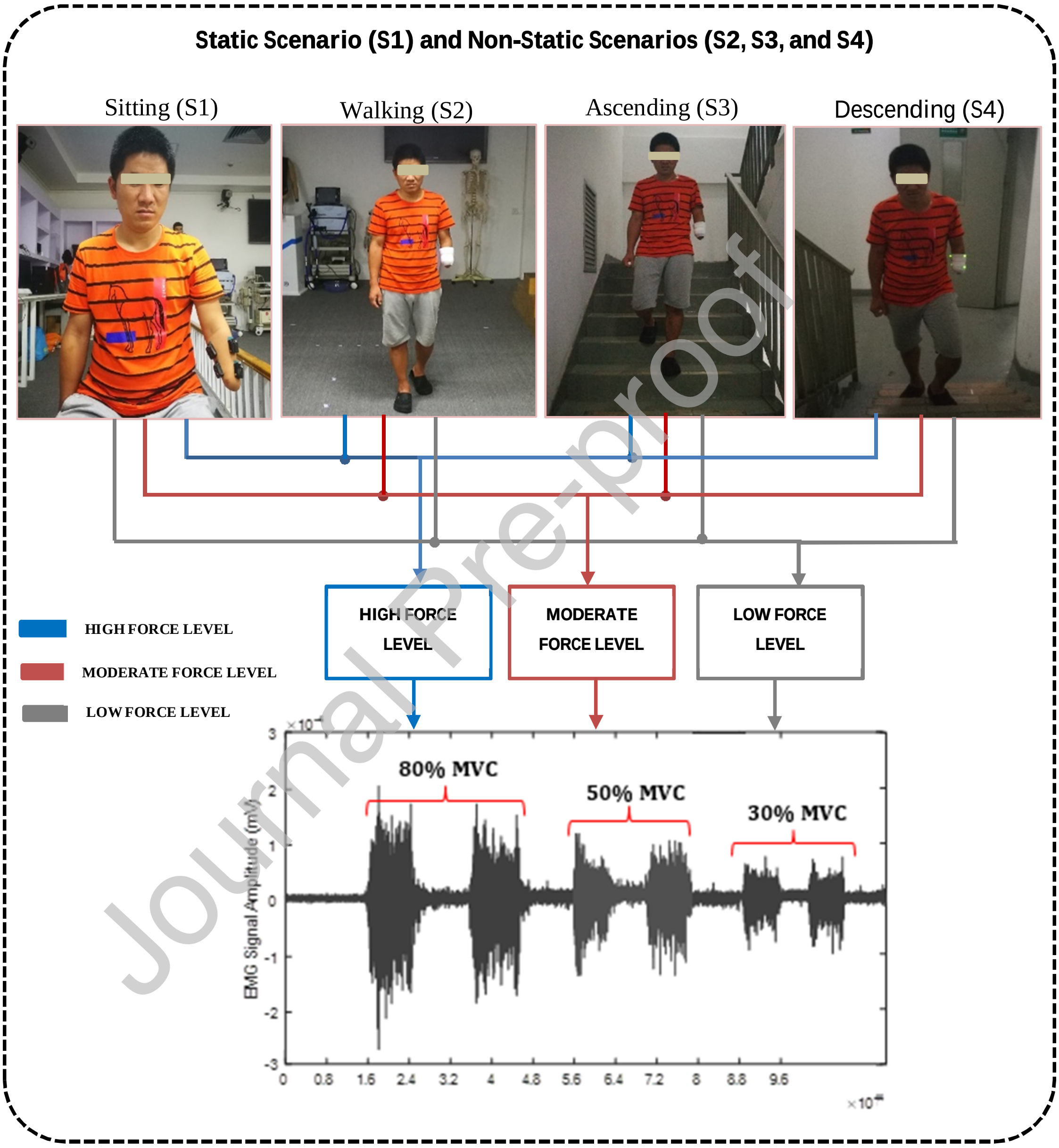

Figure 2: A representation of the experimental settings for surface EMG recordings with respect to the co-existence of MoS and MCFV factors.

In scenario S1, the subjects performed all the seven classes of targeted limb movements in a sitting posture under the described muscle contraction force levels (20%, 50%, and 80% MVC), and the corresponding EMG signals were recorded and stored for further analysis. For each specific force level, each subject performed five experimental trials (**Figure 1b**), of which each lasted for about 5-6 seconds, enabling the acquisition of sufficient data required for training and testing purposes. It is noteworthy that due to the complexity of the experiments, a rest time of about 5 seconds was introduced between successive limb movement classes to avoid muscle or mental fatigue. Also, when switching from one scenario to another, each subject was allowed to rest for approximately 5-8 minutes before continuing the experiments. These precautions were necessary to ensure the recording of high-quality signal throughout the experiments. In scenario S2, the participants performed the limb movement tasks on a flat ground of about 10 meters long while walking with an average speed of about 1.0 m/s. Meanwhile in the stairs terrain (scenario S3 and S4, characterized by 12 steps with depth and elevation of 0.25m and 0.15m, respectively), the subjects also performed the limb movement tasks while ascending/descending the stair with an average speed of 1.0 m/s. It should be noted that this was found to be convenient for the participants after a preliminary examination [10, 31], thus it was adopted. It should be noted that the recorded EMG signals were preprocessed and analyzed using MATLAB version R2017b (Mathworks, USA) programming tool.

2.4 Data preprocessing

To effectively attenuate external interferences in the acquired EMG recordings, we first applied a 50 Hz notch filter to the signal that was sampled at 1024 Hz to eliminate the inherent power line noise. After analyzing the characteristics of the resulting signals, we applied a 5th order Butterworth filter with frequency bands between 20 Hz (lower band) and 500 Hz (upper band) to further preserve the useful components of the signal [2, 39]. These procedures are often required to enhance the succeeding processes that involves extraction of informative features utilize to characterize the signal patterns and recognition of the patterns via machine learning algorithm [2-5]. It should be noted that the sampling frequency and its parameters as utilized in this study would not influence the characteristics of the extracted features across subjects since the same equipment and

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same sampling parameters were utilized in all the experiments. However, in situation where the EMG recordings are made using different equipment and sampling parameters, the characteristics of the extracted features may be somewhat inconsistent, thus resulting in degradation in performance of the pattern recognition system. Thus, one way to deal with this issue would be to ensure the usage of the same equipment and sampling parameters through the experimental sessions across subjects.

2.5 Feature extraction and classification

The choice of feature set is considered a core stage in the development of PR-based scheme for MDF prostheses control [39-42], and depending on the application requirements it can be extracted either in time or frequency domain or the combination of both [43]. In the practical settings, an ideal feature set should be invariant to factors causing alterations in EMG signal patterns, and such feature should possess the capability to maintain distinct class separability that will effectively distinguish the signal patterns of different limb movements. In this regard, an adequately robust feature extraction method is proposed to optimally characterize EMG signals in the presence of the co-existing impact of MoS and MCFV. And this would enable the realization of consistently accurate limb movement intent decoding based pattern recognition technique. Prior to the EMG feature extraction task, this study adopted a sliding segmentation technique with window length of 150ms and increment of 100ms. For the sake of clarity and proper understanding, the step-wise procedure for extracting the proposed feature set from EMG recordings to mitigate the co-existing impact of MoS and MCFV on PR-based movement intent classifier, is conceptualized in Figure 3 as follows.

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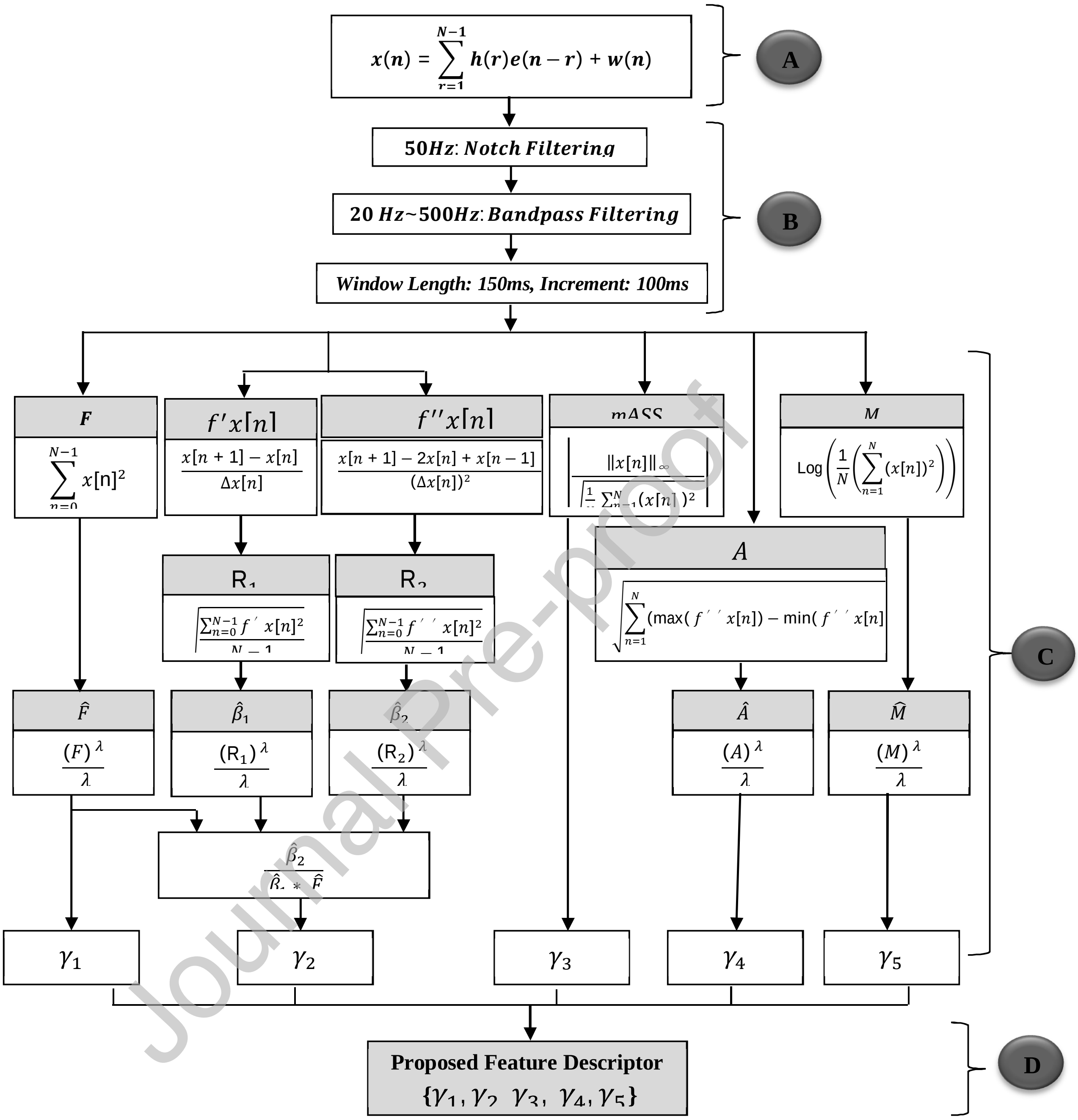

Figure 3: Conceptualization of the acquired EMG signal preprocessing and the step-wise procedure for extracting the proposed feature set. (A). A model of the Acquired EMG signal, (B). Data preprocessing steps, (C) Proposed feature extraction procedure, (D) The proposed integrated five-dimensional feature vector.

In constructing the proposed feature extraction framework as conceptualized in **Figure 3**, the following sequential steps were taken. Firstly, the acquired surface EMG signal is represented mathematically using Equation (1).

$$x(n) = \sum_{r=1}^{N-1} h(r)e(n-r) + w(n) \qquad (1)$$

where $x(n)$ denote the modeled surface EMG recordings for each class of the targeted limb movement, $e(n)$ is the corresponding firing impulse, $h(r)$ represents the motor unit action potential that denote a summation of the muscle fibers associated to a single motor unit, $w(n)$ is the zero mean additive white Gaussian noise, and N stands for the number firing motor units per time.

Given that $x(n)$ is the modeled EMG signal represented in Equation (1), and n = 1, 2, 3, … N, the feature extraction process begins with the computation of the square descriptor and its integral value ($denoted\ as\ F$) to obtain the innate energy information in different muscle contraction levels of the signal, as expressed in Equation (2).

$$F = \int_0^T x(\mathrm{t})^2 dt = \sum_{n=0}^{N-1} x[\mathrm{n}]^2 \qquad (2)$$

Here, the parameter T represents the observation time of the signal per window segment (typically 150 ms, as in Figure 3.), and N denotes the number of samples per segment used in the computation. The extracted feature, F was further normalized using a normalization technique to obtain Equation (3).

$$\gamma_1 = \hat{F} = \frac{(F)^{\lambda}}{\lambda} \qquad (3)$$

where the parameter λ is the normalization coefficient whose value was set to 0.1 . Notably, this is consistent with the Parseval's theorem which state that the energy content in a signal could be obtained by using either time or frequency-based representation of the signal [25, 27]. Hence, the normalized integral square descriptor, γ_1 holds information associated with the signal spectrum that transverses all the contraction force levels.

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To estimate the contraction force level for individual targeted limb movement while in the static scenario and at the same time discriminate the signal from inherent noise, the first and second order derivatives (f' and f'') of the signal in each analysis window were computed based on the difference between two adjacent entries of $x[n]$ as shown in Equation (4).

$$f'x[n] = \frac{x[n+1] - x[n]}{\Delta x[n]}, \qquad f''x[n] = \frac{x[n+1] - 2x[n] + x[n-1]}{(\Delta x[n])^2} \qquad (4)$$

Based on Equation (4), the first and second order square root descriptors (denoted as $\mathrm{R}x_1[n]$and $\mathrm{R}x_2[n]$) were calculated and normalized to produce $\hat{\beta}_1$ and$\hat{\beta}_2$, respectively, as shown in Equations (5) and (6). Meanwhile, a variant of the descriptors in Equations (2) and (5), have been applied to tackle a different multiple factor problem in the domain of myoelectric pattern recognition previously [27, 29, 45]. It should be noted that this study adopted the box-cox power transformation technique to normalize the extracted features and the optimal value of λ was determined by examining a range of values from -1 to +1 with a jump of 0.01 using box-cox function. Also, a previous work suggested that a value of 0.1 would be appropriate for the λ parameter [29].

$$\mathrm{R}_1 = \sqrt{\frac{\sum_{n=0}^{N-1} f'x[n]^2}{N-1}}, \qquad \mathrm{R}_2 = \sqrt{\frac{\sum_{n=0}^{N-1} f''x[n]^2}{N-1}} \qquad (5)$$

$$\hat{\beta}_1 = \frac{(\mathrm{R}_1)^{\lambda}}{\lambda}, \quad \hat{\beta}_2 = \frac{(\mathrm{R}_2)^{\lambda}}{\lambda} \qquad (6\ )$$

Where N is the sample size of the recorded EMG signal and $\lambda = 0.1$. The coefficient of regularization (represented as γ_2) that correlates with the signals in a given analysis window with respect to the contraction force for a targeted limb movement was computed using Equation (2) and (6)

$$\gamma_2 = \frac{\hat{\beta}_2}{\hat{\beta}_1 * \gamma_1} \qquad (7)$$

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Markedly, the absolute sum (*ASS*) descriptor which allows full-wave rectification of EMG signals within a specific time frame was proposed in a previous study [5]. This descriptor was improved by applying a standardization procedure to obtain an adapted version (γ_3) which obtains additional information that construct similar patterns across muscle contraction levels and subject mobility (Equation 8).

$$\gamma_3 = \left| \frac{\|x[n]\|_\infty}{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (x[n]\ )^2}} \right| \quad (8)$$

$$where\ \|x\|_\infty = \max(|x_1|, |x_2|, \ldots\ |x_n|)$$

Furthermore, for proper representation of the underlined signal patterns in different scenarios, the signal's amplitude along the first non-singleton dimension is obtained by computing the difference between the maximum and the minimum value of $x[n]$, using the second order approximate derivative and thereafter normalized as shown in Equation (9) and (10). Common-mode information across the mobile scenarios per movement class were extracted using the mean logarithm of the signal and normalized using Equation (11) and (12) respectively.

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$$A = \sqrt{\sum_{n=1}^{N} (\max(\ f''x[n]) - \min(\ f''x[n]))^2{}_n} \quad (9)$$

$$\gamma_4 = \hat{A} = \frac{(A)^{\lambda}}{\lambda} \quad (10)$$

$$M = \mathrm{Log}\left(\frac{1}{N}\left(\sum_{n=1}^{N} (x[n])^2\right)\right) \quad (11)$$

$$\gamma_5 = \widehat{M} = \frac{(M)^{\lambda}}{\lambda} \quad (12)$$

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Afterward, these features were concatenated to form a five-dimensional feature vector $(\gamma_1, \gamma_{2,} \gamma_3, \gamma_4, \gamma_5)$, which is expressed as the invariant time-domain descriptor (*invTDD*).

By using the two strategies described in Section 2.6, we investigated the extent to which the proposed *invTDD* method would minimize the dynamic co-existing impact of MoS and MCFV on PR-based system, and further compared its performances with the commonly applied feature extraction methods described as follows.

a) The time-dependent spectral domain (TD-PSD) feature set, recently proposed by Al-Timemy et al. in [29].

b) The four frequently utilized time-domain descriptors (TD4) comprising of, zero-crossings, mean absolute value, slope sign change, and waveform length [36].

c) A recently proposed two-dimensional time-domain descriptor identified as NOV in this study [5].

d) A combination of the 5th order autoregressive (AR) coefficients and the root mean square (RMS) feature denoted as TDAR in this study [37-38].

e) The root means square descriptor that has been widely considered for characterizing EMG signal patterns [2].

To decode the subjects' limb movement intent from the constructed feature matrix, two classification algorithms including support vector machine (SVM) and linear discriminant analysis (LDA) were utilized. Meanwhile, in other to reduce human interference and as well find optimal data combination five-fold cross validation technique [46], was employed for the partitioning of the extracted feature matrix into training and testing sets. The rationale behind considering these classification schemes is that their performances are relatively good, especially when considering multi-class problems [5, 8, 10, 13]. Also, previous studies have re-iterated the need to utilized optimal classification algorithm especially in the field of pattern recognition [47-48]. Thus, we built a radial basis function driven SVM classifiers, and compared its classification performance with that of the LDA classifiers. Notably, we found that SVM achieved slightly lower performance in comparison to the LDA for some subjects. The LDA algorithm runs much faster than its SVM counterpart due to its relatively simple structure and it could be easily implemented in real-time, hence it was adopted [10, 14-15].

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2.6 Data Analysis and performance evaluation

Based on the two approaches defined below, the combined impact of MoS and MCFV on EMG-PR-based motion intent predictor was systematically investigated:

a) Intra-Scenario analysis: This involves assessing the performance of the PR-based classifiers when trained and tested with data obtained from the same scenarios with respect to the different muscle contraction force levels; and

b) Inter-Scenario analysis: this involves evaluating the PR-based classifiers' performance when the training and testing data comes from different scenarios across the three muscle contraction force levels.

For both strategies, the evaluation metrics including classification error (CE), Mathew Coefficient Correlation (MCC), and F1-Score, were considered and their descriptions are given as follows. The CE, a commonly applied evaluation metric which represent the number of non-correctly identified samples over the sum of all samples (equation 13) was utilized in the current study. The MCC that has been widely applied in multiclass problem, was also adopted for evaluation in the study (equation 14). Also, the MCC is considered to be a highly informative metric for assessing classification tasks since it is considered to be a balanced ratio amongst the four confusion matrix parameters (false positives, true positives, true negatives, and false negatives) [44].

$$CE = \frac{Number\ of\ incorrectly\ classified\ samples}{Total\ number\ of\ testing\ samples} * 100\% \qquad (13)$$

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \qquad (14)$$

Where TP denotes the count of *true positives*, TN represents the count of *true negatives*, FP represents a number of *false positives*, and FN is the number of *false negatives* as obtained from a confusion matrix. In addition, F1_Score was also employed for the evaluation process which was computed based on equations 15, 16, and 17.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (15)$$

$$Precision = \frac{TP}{TP+FP} \qquad (16)$$

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$$F1\_Score = \frac{2 * Recall * Precision}{Recall + Precision} \qquad (17)$$

Furthermore, the significant different test between the proposed methods and the other feature extraction methods were performed using analysis of variance (ANOVA) of single factor with a confidence level set to $p<0.05$. Also, the Bonferroni correction approach was utilized for the post-hoc analysis.

3.0 Results and Discussion

3.1 Intra-Scenario analysis

Based on individual scenario (S1, S2, S3, and S4), we investigated how the proposed *invTDD* method mitigated the co-existing impact of MoS-MCFV on the performance of PR-based movement intent classifier, and further analyzed the obtained results in comparison to those of the commonly applied feature extraction methods in the following sub-sections. It should be noted that the analyses were done based on the combination of results obtained from the amputees and non-amputees subjects.

3.1.1 Considering EMG recordings from the static scenario (S1)

By utilizing data from S1 (sitting position), the PR-based movement classifier was individual trained per time using feature matrix obtained from each of the muscle contraction force levels (say low or medium or high), and tested with the combination of feature matrices from the three force levels. Based on the obtained results (**Figure 4a**), it can be seen that the proposed *invTDD* method achieved significantly lower CE of 9.33% (Train low: Test all), 7.36% (Train medium: Test all), and 11.27% (Train high: Test all) across subjects and movement classes in comparison to the other methods considered. Moreover, the *invTDD* recorded an average CE of 9.32% across muscle contraction force levels compared to the TD-PSD (CE = 18.17%, $p = 0.008$), TD4 (CE = 23.66%, $p = 0.029$), NOV (CE = 18.32%, $p = 0.017$), TDAR (CE = 15.42%, $p = 0.029$), and RMS (CE = 26.36%, $p = 0.016$).

3.1.2 Considering EMG recordings from the non-static scenarios (S2, S3, and S4)

The training and testing procedures employed in scenario **S1** was also applied to the data obtained from **S2** (level ground walking), and in like manner, the proposed *invTDD*

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method achieved a mean CE of 12.64%, which is much lower than that of the commonly applied TD-PSD (20.47%), TD4 (28.44%), NOV (23.11%), RMS (30.61%), and TDAR (20.14%) as presented in **Figure 4b**. This result indicates that the *invTDD* method was able to attenuate the combined impact of MoS-MCFV by achieving a substantial reduction in CE of between 7.50%~17.97% (at $p<0.05$) in scenario **S2,** compared to the previously proposed methods. By analyzing the plots in **Figure 4c** and **4d**, comparable performance trends were observed when the feature matrices constructed from the data of scenarios **S3** and **S4** (ascending and descending of stairs terrains) were employed in the training and testing of the built PR-based movement-intent classifier. Interestingly, training the PR-based system with data from the moderate force level appeared to generalize well than those from low or high muscle contraction force levels as shown in **Figure 4**. Hence, we decided to train the PR-based limb movement-intent classifiers with feature matrices extracted from the medium muscle contraction force level data and tested the classifiers using concatenated features across muscle contraction force levels for each scenario to obtain the MCC values.

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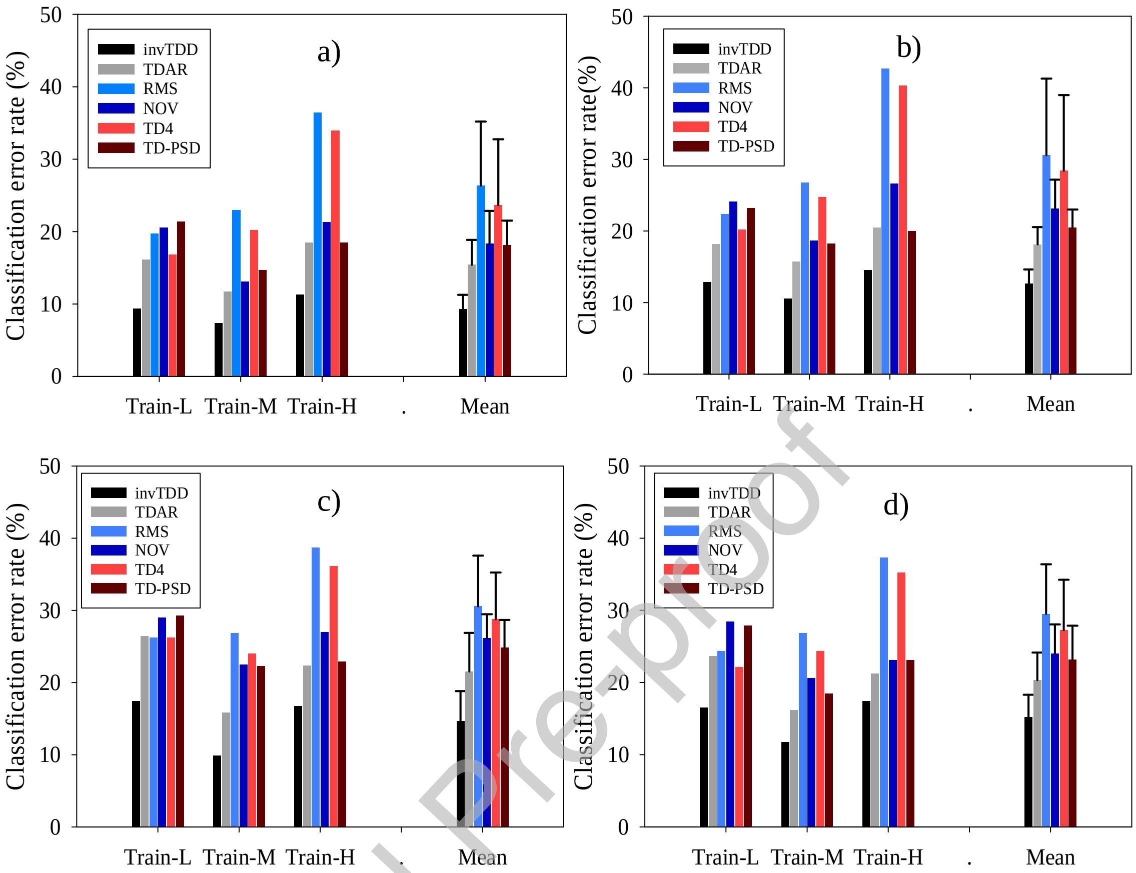

Figure 4: Intra-scenarios analysis classification results averaged across subjects and movement. Note that the data used for training is pulled from a specific muscle contraction force level while the test data include data from all muscle contraction force levels in scenario S1 (a), S2 (b), S3 (c), and S4 (d). The error-bars denote standard errors. Note: Train-L, Train-M, and Train-H, represent training with dataset from low, medium, and high muscle contraction force levels, respectively.

3.1.3 Mathew correlation coefficient analysis

After examining the combined impact of MoS-MCFV on the PR-based movement-intent classifier in the context of *Intra-Scenario analysis*, the performances of the features were further studied using the MCC metric that was defined earlier. The MCC analysis was carried out by constructing the confusion matrices that corresponds to each of the above described scenarios in section 3.1, after which their equivalent MCC values were computed. To visualize the extent to which the impact of both factors (MoS-MCFV) could be mitigated on PR-based movement intent classifier, radar charts were plotted using the MCC score of the proposed *invTDD* method and those of other methods on the basis of

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individual scenario. It should be noted that each classifier was trained with features from medium contraction force level data and tested with features extracted from all the force levels' data, and the obtained results are presented in **Figure 5a-5d**. In scenario **S1** (**Figure 5a,** using data from the sitting scenario for training and testing), the proposed *invTDD* method achieved the highest MCC score of 0.96%, indicating its superiority over TD-PSD (0.82%), TD4 (0.77%), NOV (0.83%), TDAR (0.85%), and RMS (0.74%) in the context of variation in force levels. Also, in the other three scenarios (**Figure 5b, 5c,** and **5d,** using data from the non-static scenarios for the training and testing), the *invTDD* method performed significantly better in terms of minimizing the combined effect of MoS-MCFV than the previous methods especially in scenarios **S2** (**Figure 5b**) and **S4** (**Figure 5d**).

Likewise, analysis based on F1_Score was also conducted and the obtained results revealed that the co-existing impact of MoS-MCFV was substantially mitigated by the proposed *invTDD* method with an overall F1_Score of 0.93% which is much higher than those of the other methods. Therefore, we could deduce from these results that the *invTDD* method would potentially mitigate the inherent co-existing impact of MoS-MCFV on PR-based systems compared to the other previous methods in the context of *Intra-Scenario analysis*. To provide more concise evaluation results, the RMS feature was excluded in the subsequent analyses because it achieved the least performance amongst the compared methods.

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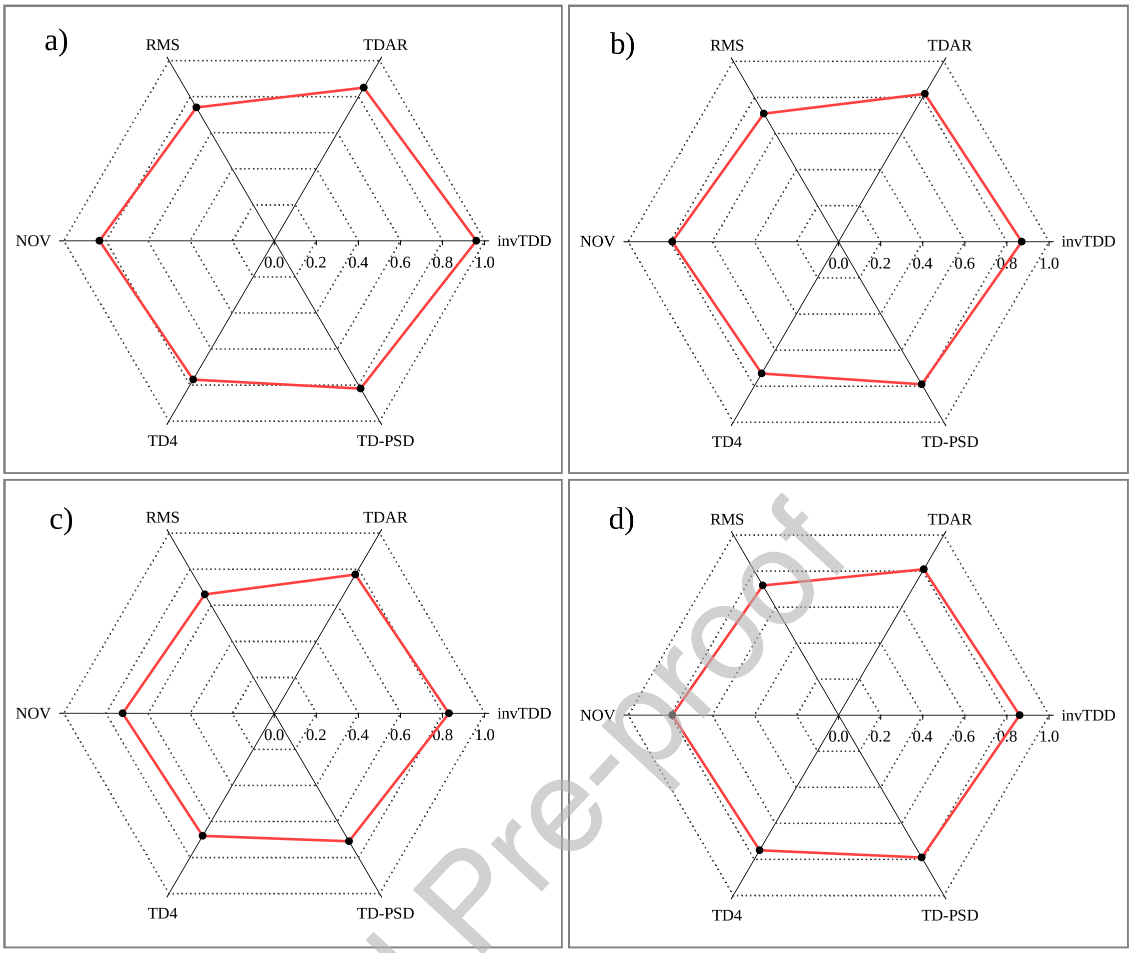

Figure 5: Intra-scenario analysis results averaged across all subjects and movement classes based on MCC metric. Note that the training data was pulled from the medium muscle contraction force level while the test data was obtained from all the contraction levels in scenario S1 (a), S2 (b), S3 (c), and S4 (d).

3.2 Inter-Scenario analysis

The co-existing impact of MoS-MCFV on the performance of the PR-based movement-intent predictor was further examined with respect to the *invTDD* and the previous methods on ***Inter-scenario*** basis (that is, across all scenarios). In this session, each classifier was constructed with the training data pulled from a particular contraction force level (for instance: 20% MVC) across S1, S2, S3, and S4 scenarios, and the test data from the other two contraction force levels (for instance: 50% MVC and 80% MVC) across all the scenarios. It should be noted that the above described training and testing data were firstly obtained based on *invTDD* method to form a feature matrix applied to characterize the signal patterns for prediction of the limb movement-intents across all the recruited subjects. Similarly, the experimental procedure was utilized to construct feature

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matrix based on TD-PSD, TD4, NOV, and TDAR, that was applied for the prediction of limb movement-intents across subjects. The average results obtained across subjects and limb movement classes are analyzed using box plots, as shown in **Figure 6**.

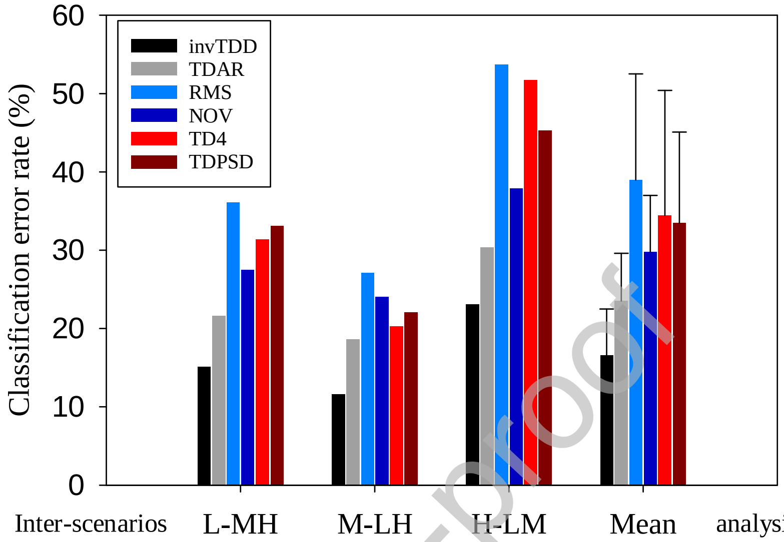

Figure 6: Inter-scenarios analysis results averaged across subjects and movement classes. The training data were obtained from a particular contraction force level across scenarios and test data from the other two contraction levels across scenario. L-MH: Training with data from FL1 and testing with data from FL2+FL3 across all scenarios, M-LH: Training with data from FL2 and testing with data from FL1+FL3 across all scenarios, H-ML: Training with data from FL3 and testing with data from FL1+FL2 across all scenarios. Note: FL1, FL2, FL3, denotes low, medium, and high muscle contraction force levels, respectively.

Based on the bar plot analysis (**Figure 6**), the PR-based limb movement-intent classifier achieved lower CE for the proposed *invTDD* method compared to the other methods for all the three cases. More precisely, for the L-MH case, the average CE of *invTDD* is 15.09% compared with the existing TD-PSD (33.02%), TD4 (31.38%), Nov (27.51%) and TDAR (21.57%), RMS (36.10%) showing significant improvement. Meanwhile, the *invTDD* recorded a standard error value of 0.91% which is also substantially lower than those of the compared methods, indicating its relatively high level of stability across subjects. Moreover, when the PR-based movement intent classifier was trained using data from the medium muscle contraction force level across all scenarios and tested using concatenation of data from the other two muscle contraction levels across scenarios (M-LH), the *invTDD* method again achieved a much lower CE of 11.60% compared to TD-PSD (22.02%), TDAR (18.62%), NOV (24.00%), and TD4 (20.27%) features, and RMS (27.11%). The invTDD feature was also observed to have recorded the lowest standard error value of 1.21% compared to the existing feature extraction methods even in the presence of the combined impact of MoS-MCFV. Also, the *invTDD* method substantially minimized the co-exiting impact of MoS-MCFV when the classifier was trained using data from high contraction force level and tested utilizing data from the other two force levels across scenarios (H-ML) as shown in **Figure 6**.

3.3 Impact of MoS-MCFV on Decoding Individual Limb Movement-Intent

It is worth noting that the above investigations were based on the average limb movement intent prediction across subjects and they do not reflect the combined effect of MoS-MCFV on the decoding of individual target limb movement. Therefore, examining the sensitivity of individual movement to the co-existing impact of MoS-MCFV could provide measures for establishing a relationship between the movement and the combined factors. Thus, further analysis on the decoding of individual limb movement was carried out when the classifiers were trained utilizing data from medium contraction force levels across scenarios and validated using data from all muscle contraction levels as shown in **Table I** and **II,** in which the seven classes of active limb movements were considered. For the non-amputee subjects (**Table I**), the *invTDD* feature was able to predict the classes of movement well when compared with other features, which further demonstrate its ability in terms of class separability. Also, regardless of the impact of the MoS-MCFV, the proposed *invTDD* could predict the individual movement classes well. Moreover, the same phenomenon was observed with the amputee subjects (**Table II**), and the proposed *invTDD* feature achieved the highest accuracy for all motion classes except for the HO class. Observing **Table I** and **II** carefully, it could be seen that the accuracy of the motion classes in non-amputee subjects was better than the amputee subjects, thus indicating that amputated limb movements are more susceptible to MoS-MCFV. For both category of subjects, the WS motion class recorded the lowest prediction accuracy suggesting its relatively higher sensitive to the combined influence of MoS- MCFV. Perhaps by adopting further training approach, alongside visual feedback scheme, the performance of the PR-based movement-intent classifier maybe further enhanced across force levels and scenarios.

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TABLE I: The impact of MoS-MCFV on Individual Limb Movement Prediction for Non-amputee Subjects

No.		invTDD	TDAR	RMS	NOV	TD4	TD-PSD
1	HO	90.18	82.10	74.10	83.53	72.65	78.10
2	HC	94.98	91.33	80.11	93.23	82.93	84.67
3	WE	88.39	84.87	71.12	85.49	73.98	81.12
4	WF	97.63	95.38	69.74	93.69	71.81	86.42
5	WP	89.61	86.77	81.11	86.67	85.63	81.10
6	WS	73.65	70.77	63.23	64.87	65.80	69.53
7	NM	94.60	90.52	89.66	95.56	90.64	72.45

TABLE II: The impact OF MoS-MCFV on Individual Limb Movement Prediction for Amputees Subjects

No.		invTDD	TDAR	RMS	NOV	TD4	TD-PSD
1	HO	86.90	88.18	66.73	82.04	69.02	58.46
2	HC	86.80	78.58	70.23	76.49	67.35	79.62
3	WE	92.63	92.11	69.22	87.10	72.35	72.72
4	WF	92.48	86.65	65.83	78.78	68.46	71.37
5	WP	81.78	71.84	60.87	74.58	62.50	80.99
6	WS	76.29	74.89	60.10	72.60	58.10	62.45
7	NM	89.16	78.99	63.23	85.94	64.20	71.60

Finally, we present the classification accuracy of the motion classes on scenarios basis, when the training set was extracted from a specific scenario (comprising of all the three levels of muscle contraction force) and tested with data from all the scenarios (**Figure 7**). The results for both group of subjects are given for the proposed *invTDD* feature due to its overall better performances as demonstrated in the previous sections. As it can be seen from **Figure 7a**, WF recorded the highest accuracy while WS has the lowest accuracy across all the scenarios, which is consistent with the results presented in **Table I**.

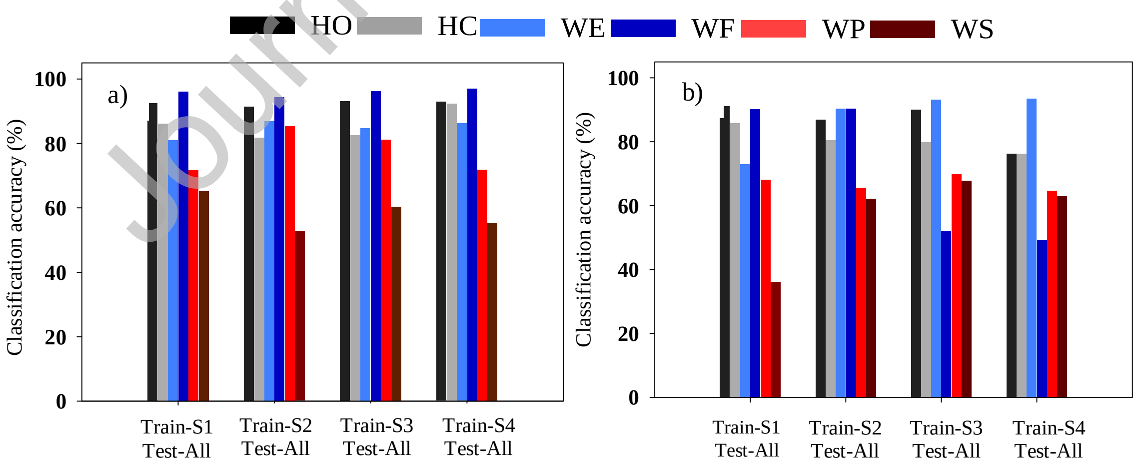

Figure 7: Scenario-based classification for individual limb movement across subjects. (a) Non-Amputee subjects, and (b) Amputee subjects.

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On the average in **Figure 7b**, WE have better accuracy when compared with the other limb movement classes and WS has the least accuracy. It is worth noting that the substantial improvement in performance achieved by the proposed *invTDD* in mitigating the combined impact of MoS-MCFV on the individual class of forearm movement intent decoding demonstrates its advantage in comparison to the other methods considered in the study.

4.0 Discussion

The development of artificial limbs with functionalities and appearances that could meet the expectations of the overwhelming majority of upper limb amputees have been a key challenge particularly from the functionality point of view [2,5,14]. In this direction, concerted efforts have been made across the academia and industry towards practical implementation of accurately robust pattern recognition-based control schemes for MDF prosthetic devices. Notwithstanding, the clinical applications of the available MDF prostheses are limited owing to the fact that they could barely offer fine-motor control capabilities that measure up to the level of intuitiveness and dexterity expected by majority of the amputees [26, 37]. Importantly, developing MDF prosthetic control schemes that would synchronize with the motor intent and smoothly execute the intended motor task is necessary to guarantee the clinical and commercial success of the device [31-34].

Towards developing an accurately robust pattern recognition-based prosthetic control scheme that could meet the above requirements, this study systematically investigated the adverse impact of two co-existing dynamic factors (MoS and MCFV) on the performances of PR-based movement intent classifier in identifying multiple classes of targeted upper-limb movements. The study was conducted based on experimental design that involved the acquisition of EMG signals associated with multiple classes limb movements using three distinct muscle contraction force levels across subjects while in a static scenario (siting) and non-static scenarios (walking on level ground, ascending a stair, and descending a stair). Additionally, we proposed the *invTDD* feature extraction method to attenuate the co-existence of MoS-MCFV on the PR-based movement intent classifier, and further compared its performances with other commonly applied methods on the bases of Intra-Scenario and Inter-Scenario analyses across different evaluation metrics.

Based on the Intra-Scenario analysis outcomes presented in **Figure 4a** (for the static scenario: **S1**), it was observed that training a PR-based movement intent classifier with dataset from a particular muscle contraction force level (for instance: low) and testing the trained model with concatenation of dataset from the other two unseen force levels (for instance: medium + high) would generally degrade the performance of the system. Interestingly, the proposed *invTDD* method was able to minimize the error by recording substantial decrease in CE ranging between 6.10% ~ 17.04% (at $p<0.05$) compared to the commonly utilized methods (TD-PSD, TD4, NOV, TDAR, and RMS). One possible reason why the proposed *invTDD* achieved significantly better results compared to the other methods even in the presence of the unseen force levels, would be because the *invTDD* integrates the $modified\ absolute\ sum\ square$ (γ_3) and *Coefficient of regularization* descriptors (γ_3) (represented with equations 7 and 8) that attempts to construct similar patterns across muscle contraction force levels when eliciting identical limb movements. Notably, when the same experiment was conducted using dataset from the non-static scenarios (**S2** or **S3** or **S4**), the performances of the PR-based movement intent classifiers were found to be much more affected (**Figure 4b-4d**), thus suggesting that the co-existence of both factors (MoS and MCFV) might lead to even more degradation in the overall performance of PR-based movement intent decoder than the individual factor. *Complimentarily, these findings supported our earlier hypothesis which stated that: the co-existence of two dynamic factors (MoS-MCFV) might profoundly degrade the overall performance of PR-based systems*. Additionally, the proposed *invTDD* substantially minimized the combined impact of MoS-MCFV on the performance of PR-based movement intent classifier compared to the commonly applied methods (**Figure 4b-4d**). In consolidation with the above observations are the results of the MCC (**Figure 5**) and F1_Score, (0.96% and 0.93%, respectively) that further showed obvious advantage of the *invTDD* in terms of attenuating the combined effect of MoS-MCFV on the performance of PR-based system. Subsequently, we found that utilizing dataset from the moderate force level (50% MVC) yielded relatively lower CEs for the *invTDD* and the other methods in comparison to dataset from the low (20% MVC) and high (80%

MVC) force levels for both the static (**Figure 4a**) and non-static scenarios (**Figure 4b-4d**), which is in line with previous findings [27]. This analysis equally suggest that the moderate force level muscle contraction would produce EMG signal patterns that maps well into the low and high force levels especially with the proposed *invTDD* method that achieved significantly lower CE (at $p<0.05$). This observed phenomenon may provide prostheses developers on the need to incorporate such knowledge into the development process.

The Inter-Scenario analysis results obtained when the PR-based classifiers were trained using data from a single force (medium) across scenarios and tested with data pulled from the other two force levels (low + high) across scenarios, showed that the co-existence of MoS-MCFV would greatly influence the overall performance of pattern recognition. Nevertheless, with the introduction of the *invTDD* method, such effect was substantially minimized compared to the previously proposed methods as shown in Figure 6. Remarkably, we also found that the performance of the *invTDD* and the other features generalized better when the classifier was trained using data from medium contraction force levels across scenarios and tested with combination of data from the low and high contraction force levels, which is consistent with the results presented in Sections 3.1.1 and 3.1.2, and also those reported in previous studies [3, 27, 30].

Moreover, the combined effect of MoS-MCFV on individual targeted limb movement was further investigated to understand how both factors would influence the prediction of each limb movement, and to what extent**.** In this regard, we firstly did the investigation using dataset from non-amputee subjects as shown in **Tables I**, with results indicating that the wrist supination and wrist pronation are the most affected limb movements in comparison to the other movements.

This phenomenon was also observed in **Table II** that shows the results of individual limb movement intent prediction accuracy when dataset from the amputee subjects were utilized. Similar trends were observed when various training strategies were examined with dataset from both the amputee and non-amputee subjects as shown in **Figure 7**. One possible explanation for these findings might be the difficulty experienced by the subjects when they attempted to modulate their forearm muscles towards eliciting the limb movements of wrist supination/pronation particularly across force levels and scenarios, which some of the subjects reported during the experimental sessions. Remarkably, by applying the proposed *invTDD* method, the degradation resulting from the co-existing impacts of MoS-MCFV on individual limb movement prediction was substantially attenuated in comparison to the other commonly applied methods (**Tables I** and **II**).

Further study based on 2-dimentional principal component analysis (PCA) technique [12], revealed that the proposed *invTDD* feature extraction method would better characterize individual targeted limb movement regardless of the co-existing influence of MoS-MCFV in comparison to the previous methods (**Figure 8**). Based on the PCA scatter plots, obvious class-separability was observed along the 1st and 2nd principal components for each class of targeted limb movement compared to those of TD-PSD, TDAR, and NOV methods (which were chosen as representative methods). This obvious class separability was especially noticed for the wrist supination (WS) and wrist pronation (WP) movements (**Figures 8a**) which again corroborate our earlier discussed results (**Figure 7**) with the exception of the last two training instances for the amputees' populations.

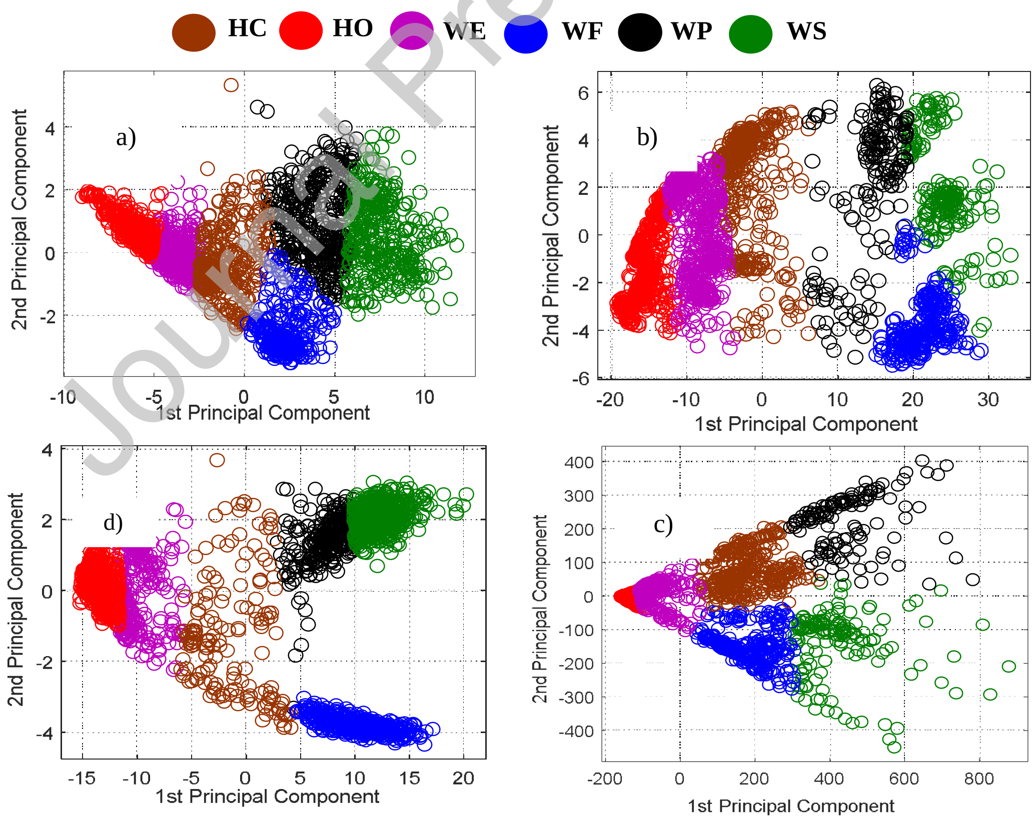

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Figure 8: PCA-based feature space analysis for each class of targeted limb movement across subjects for the proposed *invTDD* method (a), TD-PSD method (b), TDAR method (c), and NOV method (d).

We believe that such high-class separability recorded by the *invTDD* method across all the targeted limb movement classes further suggest that it might potentially aid the realization of a reliable PR-based control scheme even in the presence of multiple dynamic factors such as MoS and MCFV.

5.0 Conclusion and Future work

In summary, the dynamic co-exiting impact of MoS-MCFV on the performance of PR-based movement classifier (a rarely studied issue) was systematically investigated. Afterwards, the *invTDD* feature extraction method was proposed to optimally characterize multi-class EMG signals patterns that were subjected to both factors MoS and MCFV), and the *invTDD* method's performance was examined in comparison to other frequently adopted methods based on two different strategies (Intra-Scenario and Inter-Scenario analyses). Extensive analyses of the experimental results showed that the co-existence of MoS-MCFV would meaningfully degrade the overall performance of PR-based limb movement-intent classifier. In comparison with the other methods considered in the study, the proposed *invTDD* method significantly minimized degradations resulting from the adverse effect of MoS-MCFV on the PR movement-intent classifier, thus achieving substantial reduction in CE on both the Intra and Inter-scenario analyses. Furthermore, we demonstrated that the proposed *invTDD* method exhibits more stable characteristics than the other existing methods across subjects and limb movements even in the presence of both MoS and MCFV. Also, experimental results showed that the combined effect of MCFV-MoS would degrade the limb movement intent decoding accuracy of amputee and non-amputee subjects, but such effect was found to be more pronounced in the amputee subjects. Therefore, it is believed that the outcomes of this study would provide prosthetic developers with understanding on how to efficiently improve the clinical robustness of the state-of-the-art myoelectric control systems, especially against the co-existing effect of MoS and MCFV. Also, findings from the study are not only applicable to the upper-limb prosthetic system but may equally spur potential developments in other related areas such as intelligently driven electric wheelchairs [49], human-computer interaction systems [50], and other applications that also adopt myoelectric pattern recognition control schemes.

It should be noted that although this study investigated a crucial issue, the co-existing impact of MoS-MCFV on the performance of PR-based movement intent classifier, and proposed the *invTDD* method to resolve the issue, there are still some limitation to be addressed. In the future, we hope to further examine the accuracy and robustness of the proposed *invTDD* framework in terms of its capability to resolve other pertinent issues affecting the performance of myoelectric pattern recognition system, especially in the context of highly dexterous forearm/fine finger movements that would normally require complex neuromuscular coordination. Furthermore, we hope to consider online processing of the myoelectric data via cloud-based platform [51], towards studying the proposed *invTDD* feature set's performances with respect to the co-existing impacts of MoS-MCFV.

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Declaration of competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

[1] B. T. Carlsen, P. Prigge, J. Peterson, Upper extremity limb loss: functional restoration from prosthesis and targeted reinnervation to transplantation. Journal of Hand Therapy, 2014, 27(2), 106-114.
[2] Y. Geng, Ouyang, O.W. Samuel, S. Chen, X. Lu, C. Lin, G. Li, A Robust Sparse Representation Based Pattern Recognition Approach for Myoelectric Control. IEEE Access, 2018, 6, 38326-38335.
[3] E. Scheme, K. Englehart, Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use, Journal of Rehabilitation Research and Development 48 (2011) 643–660.

Journal Pre-proof

[4] S. Amsüss, P.M. Goebel, J. Ning, B. Graimann, L. Paredes, D. Farina, Self-Correcting pattern recognition system of surface EMG signals for upper limb prosthesis control, IEEE Transactions on Biomedical Engineering, 61 (2014) 1167-1176.
[5] O.W. Samuel, H. Zhou, X. Li, H. Wang,H. Zhang, A.K. Sangaiah, G. Li, Pattern recognition of electromyography signals based on novel time domain features for amputees' limb motion classification, Computers and Electrical Engineering 2017 (2017) 1-10.
[6] F.R. Finley, R.W. Wirta, Myocoder studies of multiple myopotential response. Archives of physical medicine and rehabilitation, 1967, 48(11), 598-601.
[7] Cho, Y., Lee, A., Park, J., Ko, B. and Kim, N., 2018. Enhancement of gesture recognition for contactless interface using a personalized classifier in the operating room. Computer methods and programs in biomedicine, 161, pp.39-44.
[8] M. G. Asogbon, O.W. Samuel, Y. Geng, S. Chen, D. Mzurikwao, P. Fang, G. Li, Effect of window conditioning parameters on the classification performance and stability of EMG-based feature extraction methods. 2018 IEEE International Conference on Cyborg and Bionic Systems (CBS), 576-580.
[9] G.R. Naik, H.T. Nguyen, Non Negative Matrix Factorization for the Identification of EMG finger movements: Evaluation using matrix analysis. IEEE Journal of Biomedical and Health Informatics (JBHI), 2015, 19 (2), pp. 478 - 485.
[10] O.W. Samuel, X. Li, Y. Geng, M.G. Asogbon, P. Fang, Z. Huang and G. Li, Resolving the adverse impact of mobility on myoelectric pattern recognition in upper-limb multifunctional prostheses, Computers in Biology and Medicine, 2017, 90, pp. 76-87.
[11] G. Li, A.E. Schultz, T.A. Kuiken, Quantifying pattern recognition-based myoelectric control of multifunctional transradial prostheses, IEEE Trans Neural Syst.Rehabil. Eng. 18 (2010) 185-92.
[12] A. Phinyomark, P. Phukpattaranont, C. Limsakul, Feature reduction and selection for EMG signal classification. Expert Systems with Applications, 2012, 39(8), 7420-7431.
[13] A. Fougner, E. Scheme, A.D. Chan, K. Englehart, Ø. Stavdahl, Resolving the limb position effect in myoelectric pattern recognition, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2011, 19(6), 644-651.
[14] G.R. Naik, D.K. Kumar, M. Palaniswami, Multi run ICA and surface EMG based signal processing system for recognising hand gestures. 2008 8th IEEE International Conference on Computer and Information Technology, 700-705.
[15] F. Ferreri, D. Ponzo, L. Vollero, A. Guerra, G. Di Pino, 2014, Does an intraneural interface short-term implant for robotic hand control modulate sensorimotor cortical integration? An EEG-TMS co-registration study on a human amputee. Restorative neurology and neuroscience, 2014, 32(2), 281-292.
[16] Coapt Engineering, Advanced Pattern Recognition Based Prostheses: https://www.prnewswire.com/news-releases/coapt-now-first-and-only-advanced-myoelectric-control-system-with-fda-class-ii-clearance-300448734.html. Date Accessed: 20180910
[17] The world's first clinically approved 3D-printed bionic arm. URL: https://openbionics.com/. Date Accessed: 15th July, 2019.
[18] Advanced upper limb prostheses technology. URL: https://www.ottobock.com/en/company/ottobock-industrials/, Date Accessed: 3rd May, 2019.
[19] O.W. Samuel, P. Fang, S. Chen, Y. Geng, G. Li, Activity recognition based on pattern recognition of myoelectric signals for rehabilitation. In Handbook of Large-Scale Distributed Computing in Smart Healthcare, 2017, pp. 427-442, Springer, Cham.
[20] X. Li, O.W. Samuel, X. Zhang, H. Wang, P. Fang, G. Li, A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees. Journal of NeuroEngineering & Rehabilitation, 2017, 14(1), 2.
[21] L.H. Smith, L.J. Hargrove, B.A. Lock, T.A. Kuiken, Determining the optimal window length for pattern recognition-based myoelectric control: balancing the competing effects of classification error and controller delay, IEEE Trans. on Neural Systems and Rehab. Eng. 2011, 9, 86-192.
[22] L. Hargrove, K. Englehart, B. Hudgins, A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control, Biomedical Signal Processing and Control 3 (2008) 175-180.
[23] A. Young, L. Hargrove, T.Kuiken, The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift. IEEE Transactions on Biomedical Engineering 58 (2011) 2537-2544.

[24] Wenfeng Li, Xinyun Hu, Raffaele Gravina, Giancarlo Fortino: A Neuro-Fuzzy Fatigue-Tracking and Classification System for Wheelchair Users. IEEE Access 5: 19420-19431 (2017).
[25] R.N. Khushaba, M. Takruri, J.V. Miro, S. Kodagoda, Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features. Neural Networks 55 (2014) 42–58.
[26] Y. Geng, O.W. Samuel, Y. Wei, G. Li, Improving the Robustness of Real-time Myoelectric Pattern Recognition against Arm Position Changes in Transradial Amputees, BioMed Research International, 2017 (2017) 1-10.
[27] R.N. Khushaba, A. Al-Timemy, S. Kodagoda, K. Nazarpour, Combined influence of forearm orientation and muscular contraction on EMG pattern recognition, Expert Systems with Applications, 2016, 61, 154-161.
[28] 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 journal of biomedical and health informatics, vol. 19, no. 3, pp.874-882, May 2015.
[29] A.H. Al-Timemy, R.N. Khushaba, G. Bugmann, J. Escudero, Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2016, 24(6), 650-661.
[30] X. Li, P. Fang, L. Tian, and G. Li, "Increasing the robustness against force variation in EMG motion classification by common spatial patterns," In Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE, pp. 406-409, July 2017.
[31] O.W. Samuel, X. Li, P. Fang and G. Li, Examining the effect of subjects' mobility on upper-limb motion identification based on EMG-pattern recognition, In Intelligent Robot Systems (ACIRS), Asia-Pacific Conference on. IEEE, pp. 137-141, July 2016
[32] D. Tkach, H. Huang and T.A. Kuiken, Study of stability of time-domain features for electromyographic pattern recognition, Journal of NeuroEngineering Rehabilitation, 2010, vol. 7, no.21, p.21.
[33] E. Scheme and K. Englehart, "Training strategies for mitigating the effect of proportional control on classification in pattern recognition–based myoelectric control," JPO: J. Prosthetics Orthotics, vol. 25, no. 2, pp. 76–83, April 2013
[34] K. Nazarpour, A. H. Al-Timemy, G. Bugmann, and A. Jackson, "A note on the probability distribution function of the surface electromyogram signal," Brain Res. Bull., vol. 90, pp. 88–91, 2013.
[35] A. Cömert, J. Hyttinen, Investigating the possible effect of electrode support structure on motion artifact in wearable bioelectric signal monitoring, BioMed Eng OnLine, 2015,14:44.
[36] K. Englehart, B. Hudgins, A robust real-time control scheme for multifunction myoelectric control, IEEE Trans. Biomed. Eng. 2003, 50 (7), 848–854.
[37] A. Phinyomark et al., Navigating features: a topologically informed chart of electromyographic features space. Journal of The Royal Society Interface, 2017, 14(137), p.20170734
[38] A.D. Chan, G.C. Green, Myoelectric control development toolbox. CMBES Proceedings, 2017, 30(1), 1-4.
[39] O.W. Samuel, M.G. Asogbon, Y. Geng, A.H. Al-Timemy, S. Pirbhulal, N. Ji,..., G. Li, Intelligent EMG Pattern Recognition Control Method for Upper-Limb Multifunctional Prostheses: Advances, Current Challenges, and Future Prospects. IEEE Access, 2019, 7, 10150 – 10165.
[40] A. Phinyomark et al., Feature extraction of the first difference of EMG time series for EMG pattern recognition, Computer Methods and Programs in Biomedicine, 177 (2) (2014) 247–256
[41] J. Li, S. Fong, R.K. Wong, R. Millham, and K.K.L. Wong, Elitist binary wolf search algorithm for feature selection in high-dimensional bioinformatics datasets, Scientific Reports, 7, pp. 4354, 2017.
[42] S. Fong, W. Song, K. Cho, R. Wong, and K.K.L. Wong, Training Classifiers with Shadow Features for Sensor-based Human Activity Recognition, *Sensors*, **17**(3), 476, 2017.
[43] Raffaele Gravina, Parastoo Alinia, Hassan Ghasemzadeh, Giancarlo Fortino: Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. Information Fusion 35: 68-80 (2017)
[44] S. Boughorbel, F. Jarray, M. El-Anbari, Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. PloS one, 2017, 12(6), e0177678.
[45] R.N. Khushaba, A. Al-Timemy, A. Al-Ani, A. Al-Jumaily, A Framework of Temporal-Spatial Descriptors-Based Feature Extraction for Improved Myoelectric Pattern Recognition, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2017, 25:10, 1821–1831.
[46] Zhelong Wang, Donghui Wu, Raffaele Gravina, Giancarlo Fortino, Yongmei Jiang, Kai Tang:Kernel fusion based extreme learning machine for cross-location activity recognition. Information Fusion 37: 1-9 (2017)

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[47] L. Wei, S. Wan, J. Guo, and K.K. Wong, A novel hierarchical selective ensemble classifier with bioinformatics application. Artificial intelligence in medicine, 83, pp.82-90. 2017.
[48] Y. Lu, X. Zhang, X. Fu, F. Chen, and K.K. Wong, Ensemble machine learning for estimating fetal weight at varying gestational age. In Proceedings of the AAAI Conf. on Artificial Intelligence (Vol. 33, pp. 9522-9527), 2019.
[49] A.Phinyomark, P. Phukpattaranont, C. Limsakul, A Review of Control Methods for Electric Power Wheelchairs Based on Electromyography Signals with Special Emphasis on Pattern Recognition. IETE Tech. Rev. 2011, 28, 316–326.
[50] T.S. Saponas, D.S. Tan, D. Morris, R. Balakrishnan, J. Turner, J.A. Landay, Enabling Always-Available Input with Muscle-Computer Interfaces, In Proceedings of the 22nd Annual ACM Symposium on User Interface Software and Technology, Victoria, BC, Canada, 4–7 October 2009; ACM: New York, NY, USA, 2009; pp. 167–17.
[51] Giancarlo Fortino, Daniele Parisi, Vincenzo Pirrone, Giuseppe Di Fatta: BodyCloud: A SaaS approach for community Body Sensor Networks. Future Generation Comp. Syst. 35: 62-79 (2014).

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