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Intelligent EMG Pattern Recognition Control Method for Upper-Limb Multifunctional Prostheses: Advances, Current Challenges, and Future Prospects

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ABSTRACT Upper-limb amputation imposes significant burden on amputees thereby restricting them from fully exploring their environments during activities of daily living. The use of intelligent learning algorithm for electromyogram-pattern recognition (EMG-PR)-based control in upper-limb prostheses is considered as an important clinical option. Though the existing EMG-PR prostheses could discriminate multiple degrees of freedom (DOF) limb movements, their transition to clinically viable option is still being challenged by some confounding factors. Toward realizing a clinically viable multiple DOF prostheses, this paper first explored the principles and dynamics of the existing intelligently driven EMG-PR-based prostheses control scheme. Then, investigations on core issues including variation in muscle contraction force, electrode shift, and subject mobility affecting the existing EMG-PR prosthetic control scheme were reported. For instance, variation in muscle contraction force and subject mobility led to degradation in the performance of the EMG-PR controlled prostheses with approximately 17.00% and 8.98% error values, respectively, which are still challenging issues among others. Thus, this paper reports core issues and best practices with respect to intelligent EMG-PR controlled prosthesis, the major challenges in implementing adaptively robust control scheme and provides future research directions that may result in the clinical realization of intuitively dexterous multiple DOF EMG-PR-based prostheses in the near future.

INDEX TERMS Amputees, electromyogram, pattern recognition, rehabilitation, upper-limb prostheses.

I. INTRODUCTION

Electromyogram (EMG) signal recorded from the residual limb muscles of amputees is an important source of control input for powered upper-limb prostheses built to restore lost limb functions. This is because EMG signal contains motor/neural information from which limb movement intent could be identified and most amputees retain the ability to generate such signals from their residual limb muscles.

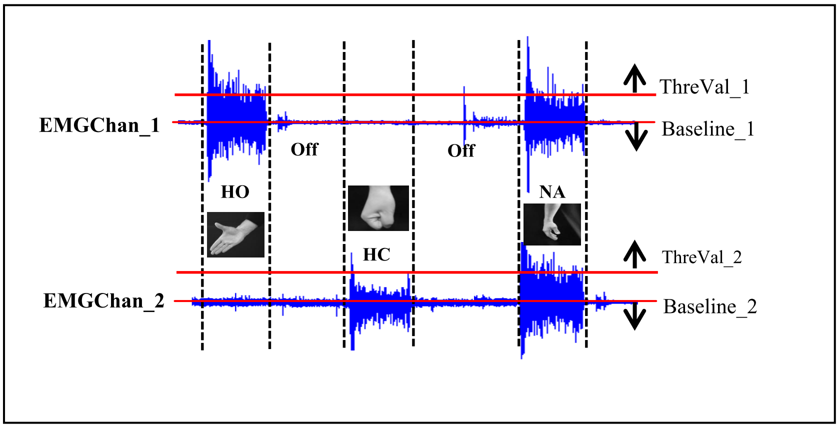

FIGURE 1. EMG control system based on the amplitudes of two-channel recordings. EMGChan_1 is the first channel placed on the flexor muscle, EMGChan_2 is the recording from the second channel placed on the extensor muscle, ThreVal_1 is the predefined threshold for the EMG amplitude in EMGChan_1, ThreVal_2 is the threshold for the EMG amplitude in EMGChan_2, HO = hand open, HC = hand close, and NA no action.

Hence, EMG signals have been considerably explored and utilized as control input to upper-limb prostheses, assistive wheel chair, assistive humanoid robot, and meal assistive robot [1]–[3]. The control method adopted in developing a prosthesis determines the functionality supported by the device, it ease of use, and acceptability [1]–[4]. Such control schemes represent a core part of upper-limb prosthesis, and the existing control methods have been categorized into two types, namely: the non-pattern recognition and intelligent pattern recognition-based control methods.

The most adopted non-pattern recognition-based prosthesis control method primarily focuses on determining the motor intent of amputees by estimation of the amplitude of EMG signal from a pair of electrodes placed on the residual arm muscles as conceptualized in Fig. 1. For instance, when the EMG signal's amplitude from one of the control site muscles is greater than a predefined threshold value (ThreVal_1) with respect to the baseline (Baseline_1), the corresponding prosthetic function (such as hand open (HO)) is selected and executed by an embedded electric motor [2]–[5]. On the other hand, when the signal's amplitude from the other control site is greater than a predefined threshold value (ThreVal_2) with respect to the baseline (Baseline_2), the associated prosthetic movement (that is hand close (HC)) is triggered. It should be noted that this control mechanism only supports single degree of freedom (DOF) movement (HO/HC or wrist flexion/wrist) per time and require selecting a pair of physiologically appropriate control muscles for each DOF (Fig.1). Thus, the mechanism only works well if the goal is to provide a single DOF function such as HO/HC. But when more DOF function such as wrist rotation is required, an external switch is needed to modulate the pair of control muscles to shift from hand mode to wrist rotation mode. Intuitively controlling multiple DOF becomes even more complex especially for individuals with high amputation level who generally have limited residual muscles [4], [7]. Apart from its support for limited DOF, the conventional amplitude- based control method is slow, cumbersome, and counter-intuitive since it involves switching from one mode to the other and users need to learn how to contract/co-contract the pair of residual arm muscles [6], [8].

While several amputees have benefitted from the non-pattern recognition-based prostheses control system, they have also been denied of the intuitiveness and dexterity associated with the natural hand functions, which may lead to secondary prostheses rejection [9]. Alternatively, the intelligent EMG pattern recognition (EMG-PR) control method was proposed primarily to address the short comings of the conventional amplitude based control method. The EMG-PR method is based on the premise that human can voluntarily activate repeatable and distinct EMG signal patterns for different motor tasks [3]. By applying efficient signal processing techniques and suitable machine learning algorithms, amputees' limb movement intent could be accurately decoded and used as control commands for multiple DOF prostheses. Recently, remarkable research efforts from the academia and industries have led to the development of intelligent EMG-PR prostheses although their clinical robustness is still being challenged by a number of critical issues that is discussed in this paper with possible solutions for future clinical applications.

In synergy with previous research efforts, we firstly studied the principles and dynamics of the existing intelligent EMG-PR based control method and how it could be improved to achieve intuitively dexterous multiple DOF prostheses that would be clinically viable. Furthermore, the paper reports core issues and best practices in EMG-PR controlled prosthesis, the major challenges in implementing adaptively robust control scheme, and provides research directions that may result in the clinical realization of intuitively dexterous multiple DOF prostheses in the near future. Hence, this study may provide potential insight on the development of advanced intelligently driven prostheses control scheme in the context of research and practical applications.

Section II of the manuscript discusses the operational principles of EMG-PR based prostheses control method with emphases on its core components. In Section III, the major challenges affecting the clinical success of EMG-PR controlled prostheses are discussed with emphases on some notable issues investigated recently. In Section IV, possible solutions on how to overcome the current clinical challenges faced by multifunctional upper-limb prostheses and their future prospects are discussed in detail while Section V concludes the paper.

II. ADVANCES IN INTELLIGENT PATTERN RECOGNITION BASED CONTROL TECHNIQUE

Intelligent EMG-PR control method has shown great potential for improved dexterity of control in upper-limb prostheses. Such control method mainly consists of five core components, which could be seen in Fig. 2. In brief, the control method involves EMG signal measurement (to capture reliable EMG signals related to limb's movement intent), signal preprocessing (to minimize all forms of noise inherent in the recordings) and data windowing, feature extraction (to retain the most discriminating information related to movement), pattern classification (to predict one of a subset of intended limb movements), and issuing control commands (translating the decoded motion into commands that drive the prosthesis). Each of these components plays an important role in determining the overall performance of the prosthetic system. Hence, the components are described in detail as follows.

A. TECHNIQUES FOR EMG SIGNAL COLLECTION

Signals from muscle contractions corresponding to upper-limb movements could be obtained by using two different methods namely invasive and non-invasive techniques. For the invasive technique, intramuscular EMG (iEMG) electrodes are employed as opposed to the non-invasive technique where surface EMG (sEMG) electrodes are used. The iEMG acquisition approach addresses some difficult challenges associated with sEMG such as maintaining robust electrode-skin contact, recording from deep muscles with minimal crosstalk, and overcoming the issue of electrode-skin impedance changes. This technique is however clinically impracticable because it requires the use of percutaneous wire/needle electrodes to transmit signals to the prosthesis [4]. In contrast to iEMG selective electrodes, sEMG electrodes can detect muscular activities from multiple muscles and thus enables the acquisition of sufficient neural information with few numbers of electrodes [5]. Moreover, previous studies have reported similar classification performance for multiple classes of forearm movements using iEMG and sEMG recordings [5], [6]. Therefore, sEMG technique remains the most viable clinical option for acquiring EMG signals in upper-limb prostheses primarily because it is non-invasive and could still offer similar performance with iEMG. Interestingly, the use of High Density surface EMG (HDsEMG) recording system enables the acquisition of signals with 2 dimensional arrays of electrodes that covers a wider area of the muscles [10]. Thus, the HDsEMG approach could provide even more efficient means of quantifying the temporal and spatial properties of the muscle activity [11], thereby addressing the limitation of the traditional single channel sEMG signal acquisition approaches.

Principally, EMG signals consist of superimposed motor unit action potentials propagated along the muscle fibers underneath the electrode surface. Thus, the placement/configuration of the sEMG electrode is an important factor especially when considering HDsEMG acquisition systems. In this regard, various types of electrode configuration schemes including Monopolar, Bipolar, and Laplacian, have been used for sEMG signal acquisition. For instance, the Monopolar configuration measures the difference between the electrode on the active site (the muscle) and a common reference electrode on non-active site (typically on bony area) [7]. In a single channel of the bipolar electrode configuration, the acquired sEMG signal represent the voltage difference between a pair of electrodes aligned across the length of the muscle underlying the skin surface [8]. Meanwhile, the Laplacian electrode configuration mostly employs a single central surface electrode with a number of neighboring electrodes, and it has been recently applied in different sEMG interfaces due to its promising nature in comparison to other configurations [12], [13].

Once the electrode configuration is decided, next is the placement of the sEMG sensors on the subject's skin. The positioning and orientation of the sensors are usually preceded by palpation of the residual arm muscles to identify the length and belly of the muscles as specified in an anatomical atlas [14]–[17]. In the case of upper-limb amputees, the residual arm muscles would be firstly examined to know exactly what muscles are left after amputation. Afterwards, the status of the residual muscles are assessed to determine if they could produce good enough EMG signals with respect to a set of pre-defined limb movements. If yes, the region where these muscles are located eventually become potential sites for sensor placement and then the electrodes are placed in line with the muscle fibers in that region. Additionally, the characteristics of the sEMG signals during pre-experimental trial is visualized through a software interface integrated with the acquisition system to ensure that the sensors are correctly placed on the arm muscles. Meanwhile, for non-amputees, the use of anatomical bony landmarks placed on the elbow or wrist is usually considered to identify potential electrode locations on their arms. With proper electrode placement, accurate detection of sEMG signals from the targeted muscles could be guaranteed without picking signals diffused from co-active adjacent or inactive muscles [18]. In addition, crosstalk (an unwanted signal picked up over a non-contracted muscle or added by co-contracted muscle(s) that often contaminate the recorded sEMG signals) could be avoided by applying proper electrode placement scheme. The positioning of sEMG electrodes over the region surrounding the neuromuscular junctions as well as movement of muscle

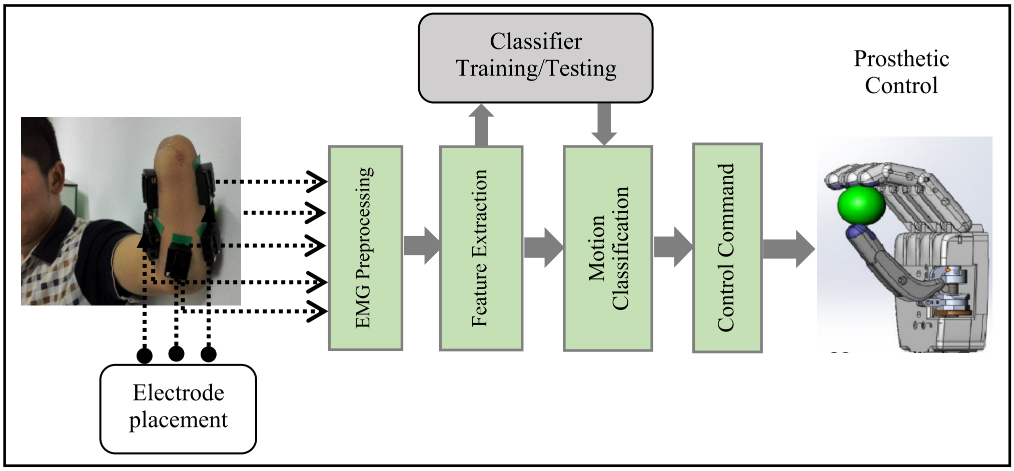

FIGURE 2. **Pattern recognition based control strategy for multifunctional upper-limb prostheses.**

underneath the electrodes can substantially alter the pattern of the recorded signals [15]. Therefore, accurate estimation of sEMG signal is subject to electrode location and failure to adhere to proper electrode placement scheme may lead to sub-optimal recordings.

To record sEMG signals, different types of hardware devices have been utilized especially the recently developed low cost Myo armband built by Thalmic Labs and the other existing acquisition system such as the Delsys Trigno Wireless, and Cometa Wave [19]. A recent study that compared the performances of six different sEMG acquisition devices shows that the Myo armband could achieve similar classification results compared to the Delsys Trigno and Cometa Wave when used for hand gestures classification. Thus, the Myo armband may be a potential choice for researchers in the domain of EMG-PR since it is relatively cheaper and offers good recordings [19], [20].

B. PRE-PROCESSING OF THE EMG RECORDINGS

Preprocessing of the raw recorded signals is a necessary step towards minimizing the inherent interference and ensuring proper analysis of the signal. To that end, different types of noises that characterize EMG signal recordings have been identified. These interferences include: noise from the acquisition equipment, ambient noise caused by electromagnetic radiation, motion artifact caused by electrode interface or movement of cables, and instability of the signals due to variation in the firing rate of motor units [21]. Typically, raw EMG signals are mostly recorded in differential mode, and with the aid of filters (band pass filters), the low and high frequency components of the signals which mostly contain less motor information are excluded. By utilizing low frequency cutoff band pass filters, baseline drift in the recordings that occur due to movement, perspiration as well as direct current offset, are often eliminated. The low frequency cutoffs usually range from 5Hz$\sim$20Hz. It is noteworthy that the mean value of the EMG recordings eventually becomes zero after being subjected to band pass filtering since the filters automatically removes the low frequency components thus forcing the mean to approximately zero or even zero in most cases. The high frequency cutoff filter eliminates the high frequency noise and prevents aliasing from occurring in the sampled signal. The cutoff frequency of the filter is quite high such that rapid on-off burst of signal can be clearly identified. Thus, the cutoff frequency range is between 20Hz$\sim$450Hz. Also, power-line interferences inherent in the recordings are usually attenuated by using either a 50Hz or 60Hz notch filter depending on the power grid specification of the country/region.

After applying band pass filtering to eliminate the high and low frequency components of the signals that may hold less information related to limb movement intentions as well as attenuating the power-line interferences, then the resultant signal is segmented into series of analysis windows prior to feature extraction.

C. EMG DATA WINDOWING SCHEMES

Upon successful cleaning of the signals, there is a need for real-time analysis, and such analysis could be best performed on time segments of the signals namely analysis window [22]. It should be noted that the instantaneous value of the preprocessed EMG signal is generally considered as non-useful input for pattern recognition techniques due to its random nature [23]. Thus, a window of the preprocessed data is required from which descriptive features are extracted [24]. Therefore, two different kinds of windowing techniques namely, overlapping window and adjacent window have been proposed for producing segments of the preprocessed signal needed for feature extraction and other kinds of analysis in pattern recognition-based systems [25]–[27]. In the latter approach, a predefined length of consecutive window segments are utilized for analysis and the feature extraction tasks. Owing to the available high-speed processors, the processing time is often less than the duration of time

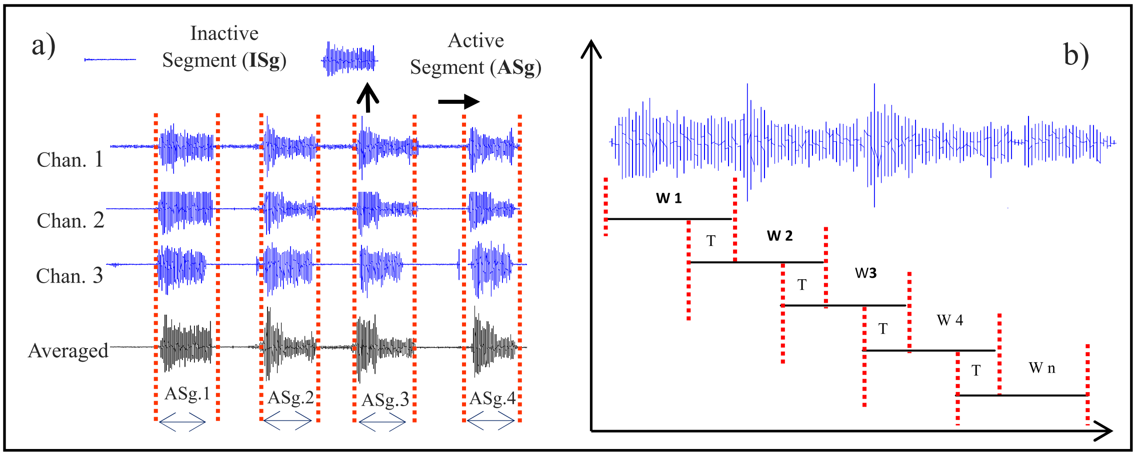

FIGURE 3. **The active segments of EMG signals from randomly selected channels during a hand close task and the sliding window segmentation scheme using the obtained active EMG data.**

segment, which makes the processor idle for certain amount of time, leading to underutilization of the processor resources. Whereas, in overlapped window approach, the idle time is utilized to acquire more data thus leading to full utilization of the processor's resource. In other words, the overlapping windowing technique utilizes the above described idle time of the processor to produce more classified outputs. In this technique, the preceding window slides over the current window with an increment time that is less than the window length itself. Fig. 3a shows the segmentation of contraction/non-contraction per motion class and the contraction segments are averaged across all the channels. The overlapping window technique has been conceptualized in Fig. 3 where each segment overlaps the previous one. It is noteworthy that the overlapping window method is more appropriate in myoelectric control systems since it tends to produce better classification decision and at the same time reduces the length of the maximum delay [28]. In principle, the length of the overlapping window per time determines the amount of EMG data used for feature extraction and other forms of analysis to achieve a single class decision for a targeted limb movement [26], [27]. Thus, to estimate the intended motion class from each sliding window in real-time, continuous classification is done using the data in the corresponding window. Smaller window increments would generally lead to a more dense but semi-redundant stream of class decisions that could improve response time and accuracy [26]. The idea of overlapping the analysis window is often adopted to maximally utilize the continuous stream of EMG data that produces a decision stream that is as accurate as possible with respect to the available computing capacity. In that case, the operational delay in real-time control due to data buffering would simply be the duration of the overlap instead of the window length which has been previously verified by Englehart and Hudgins [26]. Using a larger window length would results to more features with relatively lower statistical variance and high classification accuracy. However, such larger window lengths would lead to an observable delay in the classifier's decision which may be frustrating to the user of the prosthetic device. Thus, it is important to utilize a window length that could yield an acceptable delay in real-time. Hence, an optimal window length of between 150ms∼250ms was suggested in [24], while a length of 250ms was suggested by Englehart and Hudgins [26]. And window increment in the range of 50ms∼100ms have also been suggested in [28].

D. CHARACTERIZATION OF EMG SIGNAL PATTERNS

After segmenting the preprocessed EMG data, a set of features containing rich neural information that could aid the decoding of multiple classes of upper-limb movements are often obtained from each analysis window. Proper extraction of features from the preprocessed data would eventually lead to high performance in terms of motion recognition and stability of the prosthesis control. With the aid of mathematical or statistical models, the high dimensional raw preprocessed signals are mapped into low dimensional space by applying a suitable feature extraction algorithm. Such low dimensional feature vector basically helps to describe the information content of the signal more efficiently than the direct raw preprocessed high dimensional EMG signals which may be random and complex [26], [27]. Due to the relatively smaller size of the feature vector, the classification algorithms predicts the limb movement intent faster, thus improving the overall real-time performance of the prosthetic control system. Additionally, such informative feature vector would better characterize the signal patterns leading to consistently high classification accuracy. Considering the significant role that feature extraction plays, dozens of previous studies have attempted extracting feature sets from time-domain, frequency domain, time-frequency domain, and spatial domains for limb movement intent prediction [29].

In this direction, a range of feature extraction methods have been proposed across the different domains.

Recently, a set of feature consisting of waveform length ratio, irregularity factor, sparseness, first spectral moment, second spectral moment, and fourth spectral moment known as time dependent power spectral descriptors (TD-PSD) was proposed by Al-Timemy *et al.* [30] for better recognition of EMG signal patterns. Samuel *et al.* [31] also introduced a combination of new simple but effective time-domain features that considers the absolute value of the summation of the exp$^{\text{th}}$ root and the absolute value of the summation of square root of the data across a set of analysis windows. Furthermore, Khushaba *et al.* [32] recently proposed a set of temporal-spatial descriptors for improved characterization of EMG signal patterns. Hudgins proposed the use of four different time-domain features for limb-movement intent decoding. The features include mean absolute value, waveform length, zero crossings, and, slope sign changes. It is worthy to note that Hudgins time-domain feature set is arguably the most adopted till date in the field of myoelectric pattern recognition [33]. Meanwhile, other previously proposed feature extraction methods includes: Fast Fourier transform (STFT) based features [34], [35], wavelets based features and wavelet packet transform (WPT) based features [34], cepstral coefficients (CC), Willison amplitude (WAMP) [36], sample entropy (SampEnt) [37], reduced spectral moments (RMOM), cardinality feature [38], EMG synergies by matrix factorization analysis [39], [40], and autoregressive (AR) model parameters [41]. In general, time-domain features exhibit simple characteristics compared to frequency-domain or wavelet based features and they mostly require little computing resources, thus achieving similar performance as features in the other domain. Therefore, this is one reason for their wide adoption in myoelectric controlled systems. Importantly, the choice of feature set is considered the most significant aspect of myoelectric control because its effect on classification accuracy is found to be even greater than the type of classifier adopted [6]. Meanwhile, the feature space quality is determined based on their different properties as previously reported which include: maximum class separability, robustness, and computational complexity [42], among others. It should be noted that a high quality feature space would normally yield clusters with maximum class separability or a minimum overlap, thus minimizing the misclassification rate.

Feature sets characterized by relatively good maximum class separability are said to be more reliable especially in applications where high accuracies are required. The robustness of a feature set is described based on its ability to preserve cluster separability in the presence of noise. Also, the computational complexity of the feature set should be as low as possible to facilitate its implementation with reasonable hardware resources in real-time particularly in prosthetic control systems where rapid responses are required. Considering that several state-of-the-art feature sets have been proposed, deciding the optimal EMG feature set has been a challenging task, leading to the development of feature selection algorithms including the recently proposed Mapper based method [41], the conventional sequential forward selection (SFS), and differential evolution feature subset selection method [43] among others. By using this kind of methods, optimal feature set can be easily identified among the pool of available feature extraction methods. Also, it should be noted that different feature reduction methods including principal component analysis (PCA), uncorrelated linear discriminant analysis (ULDA), orthogonal fuzzy neighborhood discriminant analysis (OFNDA), as well as spectrum regression have been utilized to obtain smaller size of feature set that would minimize the computation cost and yield good classification results.

E. MOVEMENT INTENT DECODING

Intelligent pattern recognition-driven control methods assumes that a machine learning classifier has the capability to recognize input values (feature vector) introduced during the training phase and assign the input values to their corresponding target motion classes during the testing phase. By extending the number of DOFs and increasing the intuitiveness of control commands, intelligent pattern recognition methods offer important improvements in myoelectric control systems with several classifiers investigated and compared [28]. Having extracted the target feature set, a classification scheme is built, trained, and tested using the obtained feature vector to predict the limb movement intent upon which control commands are generated. As earlier explained, apart from the feature extraction method adopted, the choice of classifier would also influence the performance of an EMG-PR based system. Detailed description of the most commonly adopted classifiers in myoelectric interfaces is given in [27] and [44]–[47]. Nonetheless, several comparative studies agree that with an appropriate feature set and sufficient number of EMG channels, most classifiers would achieve relatively similar classification accuracy [6], [48]. This indicates that appropriate feature representation makes the classification task a linear problem. Hence, recent trend seems to be towards classifiers that are simple to implement, fast to train, and meet real-time constraints, such as the liner discriminant analysis (LDA) [5], [49]–[51], support vector machines (SVM) [52]–[54], Extreme learning machines (ELM) [55], hidden Markov models (HMM) [56]–[58], random forest (RF), and k-nearest neighbors (kNN). Amongst these classifiers, the LDA scheme is the most widely adopted in the field of myoelectric control. Meanwhile, the SVM scheme has equally gained wide applications (due to its kernel trick characteristic) as well as the kNN classifier (due to its non-parametric nature).

Notably, only few number of studies have compared the ability of the classifiers to discriminate EMG signals in long-term use and with additive artifacts or noise [59]–[62]. It can be assumed that linear classifiers are more capable to maintain high prediction accuracy compared to their nonlinear counterparts because of their better capability to generalize well on the EMG data. Kaufmann *et al.* [62] demonstrated this by showing that LDA classifier was the most robust against the long-term effect of fluctuating EMG signals when compared to five state-of-the-art classifiers. By utilizing EMG data recorded over a period of 21 days, 82.37% classification accuracy was recorded by LDA when trained with recent data and 78.73% when trained with data collected only during the first day. Young *et al.* [50] found that the LDA classifier also outperforms the multilayer perceptron (MLP) classifier in the presence of electrode shifts. However, more complex classifiers may be appropriate in long-term use where there is need for accurate classification of novel patterns during online training. Further, towards improving the classification performance, robustness, and usability of EMG-PR systems, as well as to overcome the limitations of the conventional EMG control methods, post-processing strategies such Majority Voting [63], Bayesian Fusion (BF) [64], self-correcting schemes and rejection-based methods have been proposed [65], [66].

The idea of targeted muscle reinnervation (TMR) which represent a significant breakthrough was introduced about a decade ago by Kuiken *et al.* [67] and Huang *et al.* [68] to enable individuals with high level amputation generate sufficient EMG signals for limb motion intent decoding in EMG-PR prostheses. Although TMR led to the generation of more EMG signals but the concept is yet to be fully implemented in multiple DOFs prostheses for either clinical or commercial use due to a number of challenging issues. Meanwhile, the existing EMG-PR prostheses does not support simultaneous control of multiple DOFs [69], which prevents users from having the natural feel of coordinated joint control while using the prosthetic device. Although advanced prosthetic arms including multiple DOFs wrist, offer the mechanical means to restore arm movements, there is need for systems that enable simultaneous control of such devices. Towards developing a simultaneous prosthetic control scheme, various methods have been proposed in the recent years. These approaches include the use of artificial neural networks for joint kinematics predictions [70], analysis of the muscle synergies underlying a range of upper limb movements [71], and the utilization of joint kinetics [72] amongst others. Despite the progress made, development of multiple DOFs prostheses that could aid the simultaneous control of multiple joints in a coordinated manner is rare till date.

To provide researchers with an avenue to compare the performances of their control algorithms with other existing EMG-PR based prostheses control methods, benchmark databases have been made available. For instance, the Ninapro database (http://ninaweb.hevs.ch/) [73] is considered a useful resource which provides benchmark EMG dataset of upper limb movements for testing machine learning algorithms in the context of hand prosthesis control. Additionally, a myoelectric control toolbox (http://www.sce.carleton.ca/faculty/chan/index.php?page = matlab) and BioPatRec (http://code.google.com/p/biopatrec) are open source software platforms that offers researchers the opportunity to conduct studies in the field of EMG-PR for limb movement intent decoding. And these tools would help researchers in the field of EMG classification methods to have a common methodology to compare theirs' with [74].

III. MAJOR CHALLENGES TOWARD CLINICAL ROBUSTNESS

In practice, the usability of upper-limb prostheses is influenced by several factors including intuitiveness of the integrated control mechanism, capabilities of the device, fit of the socket, and weight of the device among others. In the recent years, concerted efforts across the academia and industry have brought about significant advancement in EMG-PR based control for multiple DOF prosthetic devices. Despite the considerable progress made, pattern recognition based control methods are still being challenged by some confounding factors that are currently limiting the clinical robustness and overall success of the available multiple DOF prostheses [75], [76]. The main critical factors were investigated and reported in this study as follows.

A. EFFECT OF MOBILITY ON EMG-PR SYSTEM

Ideally, EMG signal associated with various limb movements is frequently recorded while subjects maintain static position (seated or standing) and sometimes with their elbow or arm resting on a chair or table. In such a scenario, the participants can easily produce repeatable muscle activation patterns across trials when performing targeted limb movements [77]. Thus, such laboratory experimental setting often result in high and consistent accuracy simply because the training set as well as the testing set are recorded while the participants assume static position that would allow them produce consistent muscle contractions across trials for targeted limb movements. Nevertheless in clinical practice, the situation is somewhat different because prostheses users are not only expected to use the device in static scenarios (sitting, as shown in Fig.4a) but sometimes in non-static scenarios such as walking on a flat ground (Fig. 4b), descending a stair (Fig. 4c), or even ascending a stair (Fig. 4d).

Therefore, subject mobility has been reported previously to have significant effect of about 11.35% reduction in the performance of EMG-PR motion classifier when EMG data from able-bodied subjects was considered [25]. Another recent study by Samuel *et al.* [77] investigated the effect of mobility on hand and wrist motion data (7 classes of limb movements) collected across six upper-limb amputees based on EMG-PR method and found that mobility would meaningfully degrade the classification performance of EMG-PR based control with respect to the results analyzed in Fig. 5 [77]. The results show that when EMG data from the amputated limb was used as the LDA classifiers' input, the intra-scenario classification errors (CEs) were much lower than the inter-scenario CEs (Fig. 5a). And an average intra-scenario CE of 9.50% $\pm$ 1.08% in comparison to 18.48% $\pm$ 3.39 for the inter-scenario case across subjects was recorded, resulting in an inter-scenario CE that is approximately 1.94 times higher than the intra-scenario CE (Fig. 5a). Similarly, using the

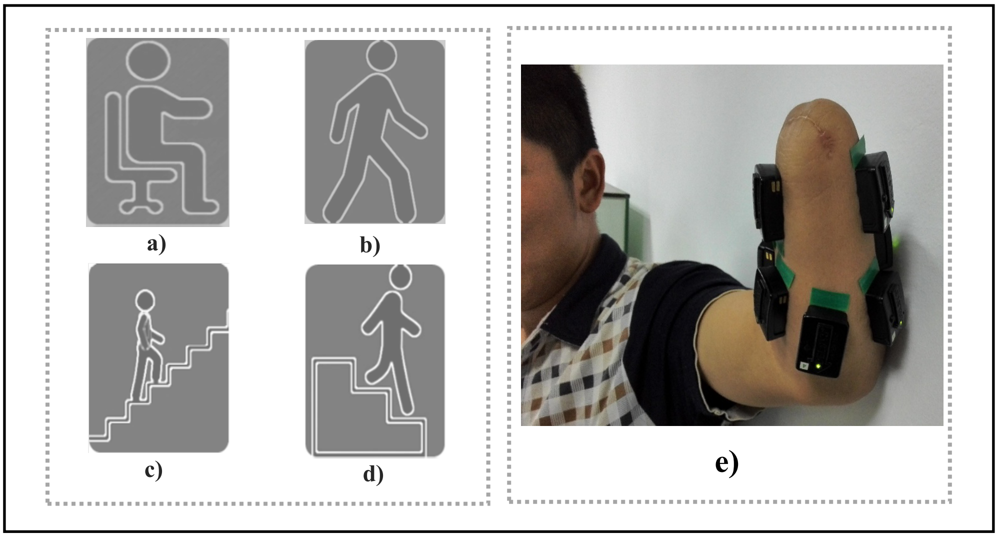

FIGURE 4. The different scenarios assumed by the participants during which EMG signals corresponding their limb movements were recorded. a) Acquisition of data in sitting position (S1). b) Collection of data while walking on a flat ground (S2). c) Collection of data while ascending a stair (S3). d) Collection of data while descending a stair (S4). e) Electrode placement on the residual arm of a transradial amputee subject.

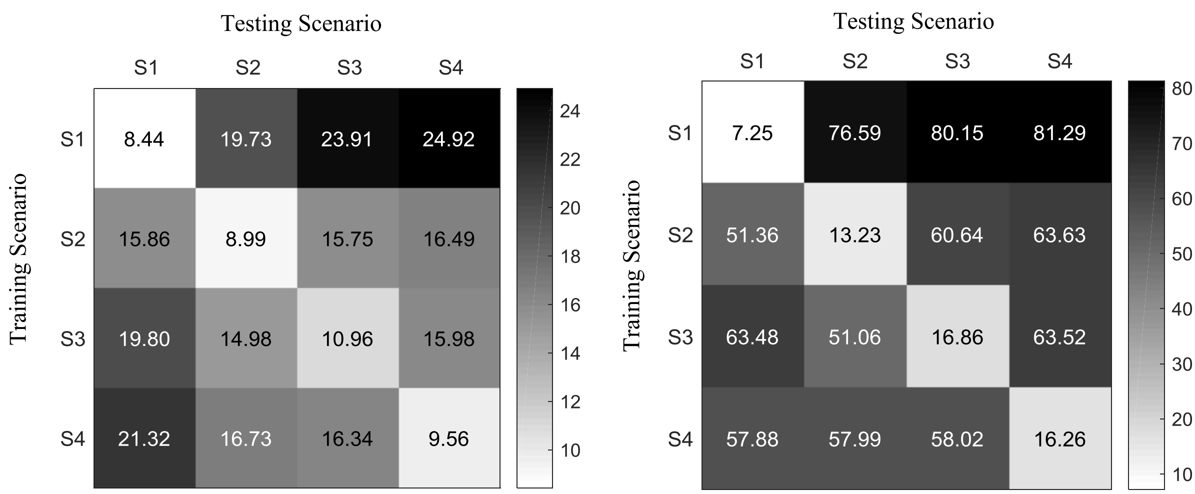

FIGURE 5. Mean motion CE across subjects with respect to the four scenarios (S1, S2, S3, and S4) using recordings from the amputated arm. a) Result obtained when EMG data was used input to LDA; b), Results obtained when ACCmmg data was used as input to LDA.

accelerometer mechanomyography (ACCmmg) data from the amputated limb, an average intra-scenario CE of 13.40% $\pm$ 4.39% as against 63.80% $\pm$ 10.29% for the inter-scenario CE was recorded (Fig. 5b). Also, the inter-scenario CE was found to be 4.76 times higher than the intra-scenario error with ACCmmg. The obvious differences observed between the intra-scenario and inter-scenario CEs were found to be mostly due to the effects caused by the mobility of subjects during the experiment. By considering the off-diagonal classification errors in Fig. 5b, it can be seen that ACCmmg recorded much larger errors indicating that it would be more susceptible to mobility compared to EMG that had lower error rates in the off-diagonal entries (Fig. 5a). Thus, ACCmmg could be used as a potential signal to distinguish between the static and non-static scenarios.

Towards attenuating the effect of mobility in decoding amputees' limb motion intentions, three possible training methods namely the Dual-stage sequential strategy, Multi-scenario training strategy, and Hybrid training strategy, were proposed and examined [77]. The Dual-stage sequential strategy consists of two stages of five sequential classifiers in which the first stage is made up of a scenario classifier built to identify each of the scenarios (S1, S2, S3, and S4) assumed by the subject per time with respect to the ACCmmg recordings. In the second stage, four different limb motion classifiers were built with each corresponding to a specific scenario that a subject assumes per time. Then, each of the four motion classifiers was trained with EMG data acquired from all the classes of motions performed in the corresponding scenario. The Multi-scenario training strategy is built by including all the possible samples of EMG signals into the training set and some previous studies had attempted to develop a somewhat similar method to address other problems [79], [80]. While the Hybrid training strategy is designed using more training information related to the arm motions of the subjects with both kinds of signals (EMG + ACCmmg) combine together.

The results of the three proposed training strategies are shown in TABLE 1 (based on data amputated limb dataset) and TABLE 2 (based intact limb dataset). Meanwhile, the analysis in TABLE 1 and TABLE 2 show the performance of the three proposed strategies in minimizing the effect of subject mobility on EMG-PR motion classifier using data from the amputated limb and intact limb, respectively.

TABLE 1. Performance in terms of classification error (%) of the proposed methods towards attenuating the effect of subject mobility on EMG-PR motion classifier using EMG data from of the amputated limb.

Scenarios	*Inter-scenario*	*DSS*	*HTS*	*MSTS*
S1	20.92	10.67	10.09	13.72
S2	16.59	9.69	11.94	13.56
S3	17.79	13.19	15.11	15.19
S4	18.63	11.90	13.52	14.08
Mean	18.48	11.36	12.67	14.14

TABLE 2. Performance in terms of classification error (%) of the proposed methods towards attenuating the effect of subject mobility on EMG-PR motion classifier using EMG data from of the intact limb.

Scenarios	*Inter-scenario*	*DSS*	*HTS*	*MSTS*
S1	19.24	9.80	10.42	12.55
S2	16.10	9.28	12.05	13.04
S3	17.66	11.67	13.44	15.02
S4	18.16	10.92	12.49	13.67
Mean	17.79	10.51	12.10	13.57

Note: DSS=Dual-stage sequential strategy, MSTS = Multi-scenario training strategy, HTS = Hybrid training strategy.

The Inter-Scenario CE was used as the baseline for comparison in both TABLES 1 and 2 across the four scenarios. And the mean for each of the proposed method was computed to determine the reduction in error achieved by the methods for amputated and intact limb datasets across subjects. Therefore, by applying the Dual-stage classification scheme, the motion CE was observed to be significantly minimized across subjects/limb motions in comparison to the inter-scenario CE as presented in TABLES 1 and 2. A mean reduction in CE of approximately 7.12% and 7.28% were respectively obtained for the amputated and intact limb. Note that the inter-scenario CEs were used as baseline for comparison in all the three proposed strategies shown in TABLES 1 and 2. Meanwhile, the Multi-scenario training strategy minimized the inter-scenario errors by 4.34% across all the scenarios for the amputated limb while for the intact limb, a decrease of 4.22% across all the limb motions and scenarios was achieved (TABLES 1 and 2). Also, the Hybrid training strategy minimized the CE by about 5.81% across all the scenarios for the amputated limb and about 5.69% for the intact limb. In summary, the three proposed training strategies were able to minimize the degradation in classification performance on EMG-PR motion classifier caused by subject mobility. However, these training strategies would normally require a participant to undergo several sessions of training to be able to obtain reasonable performance especially in real-life application which is still a challenge.

B. VARIATION IN MUSCLE CONTRACTION FORCE

During daily life activity, different muscle contraction force may be required in accomplishing the same limb movement tasks across different conditions. Thus, variation in muscle contraction force while executing the same targeted limb movement would obviously result in disparity in myoelectric signal patterns for that particular movement. Since pattern recognition based control solely rely on clustering repeatable patterns of EMG activities into discernible classes of limb movement, varying the muscle contraction force would inevitably affect the control performance of EMG-PR based prostheses. One reason for this is that, contractions performed at different force levels for specific limb movement may present a challenge to the pattern classifier thus leading to degradation in the overall classification accuracy of the system.

In line with previous studies, we further demonstrated here the impact of variation in muscle contraction force on the performance of EMG-PR based classifier. To that end, we performed the data collection tasks by conducting experiments in which five able-bodied subjects performed seven different classes of upper limb movements using three distinct muscle contraction force levels defined as follows: Low force level (20% of the maximum voluntary contraction (MVC)), Medium force level (about 50% of the MVC), and High force level (typically around 80% of the MVC) as in Fig. 6b. Meanwhile, the limb movements included hand close (HC), hand open (HO), wrist extension (WE), wrist flexion (WF), wrist pronation (WP), wrist supination (WS) and no movement (NM).

By considering the first two representative trials of the HC movement, we observed that the amplitude of the waveform for low force level is about $0.5\text{x}10^{-4}$ mV (at 20% MVC), approximately $1.0\text{x}10^{-4}$ mV (at 50% MVC) for the moderate force level, and about $1.5\text{x}10^{-4}$ mV (at 80% MVC) for the high force level as shown in Fig. 6. This indicates that the limb movements were performed with the designated force levels, thus guaranteeing the validity of the subsequent analyses. To examine the effect of variation in force level on the performance of EMG-PR based classifier, we firstly

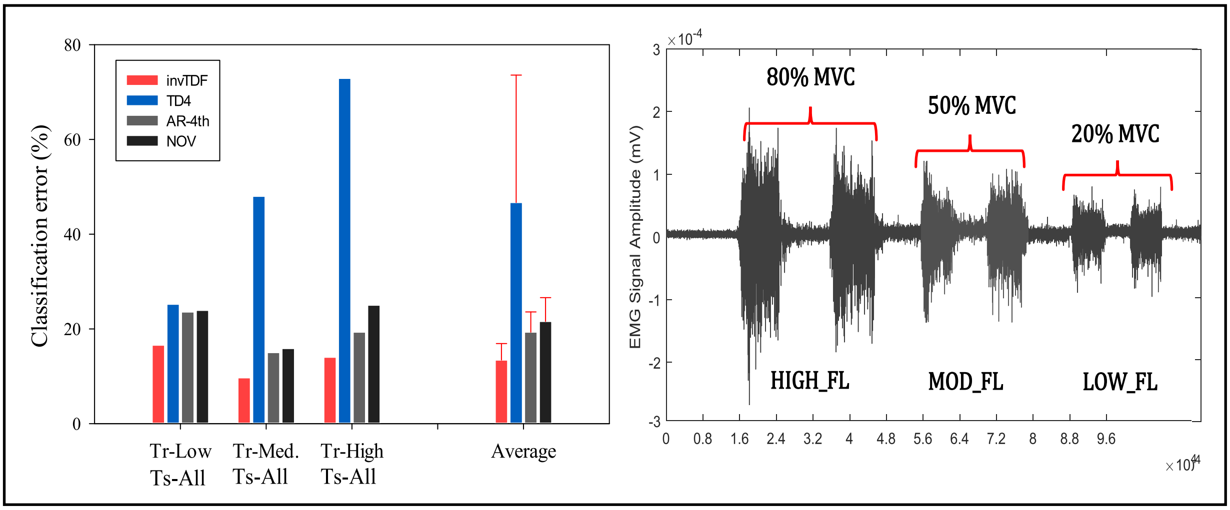

FIGURE 6. **Mean Classification performance across all subjects with training data from one muscle contraction force level and testing data from all the muscle contraction force levels.**

extract different types of features from the EMG recordings of each force level. And the extracted features includes our proposed time-domain feature set that is invariant to force variation (invTDF), Huggins feature set (TD4), Fourth order autoregressive coefficient (AR^{4th}), and a recently proposed two dimensional TD feature set denoted as NOV [81]. Subsequently, we trained an LDA classifier using the features extracted from the data for each force level and tested the classifier with aggregation of features from data across the remaining three force levels (Fig. 6). As shown in Fig. 6, training the LDA classifier with feature set extracted from EMG data collected from a particular force level (for example low) and testing the classifier with features extracted across all the force levels led to degradation in classification performance, which corroborate reports from [81]. The classification error rate was observed to be much higher when training with data from low force level compared to the other two force levels which indicate that it is difficult for subjects to naturally produce consistently low level muscle contractions. Also, high level muscle contractions often produce tremor that may result to degradation in performance of the EMG-PR system. Unlike the low and high force levels, the moderate force level was observed to have the least classification error using the four different feature extraction methods as shown in Fig. 6. This suggest that the subjects tend to consistently activate their muscles with moderate force level while performing different forearm movements. With the exception of our recently proposed feature set, it is obvious that the presence of contractions from unseen force levels actually increased the overall classification error considerably to the point where the system may be unusable (about 20% error) in real-life application. It should be noted also, that the TD-PSD feature proposed by Al-Timemy *et al.* [30] was applied to minimize the degradation in classification caused by variation in muscle contraction force level and a reduction in CE in the range of 6% to 8% was achieved. Other researchers have considered attenuating the effect of variation in force levels on the performance of pattern recognition based prostheses control by using training strategies that attempts to include samples from all possible force levels. With such training strategies, an error of about 17% was achieved, which is still not ideal in real life application. Another challenge with this method is that the prosthesis user would need to undergo an extensive training session that would require data samples from all possible force levels, especially if they are to do this daily to accommodate electrode shift while donning the prosthesis. This kind of method will eventually lead to significantly longer training time/phase which may limit the clinical viability of pattern recognition based prostheses.

C. VARIATION IN LIMB POSITIONS DURING TARGETED MOTION

The practical use of upper-limb prosthesis during activities of daily living would require the limb to move through a range of workspace leading to the limb assuming different positions. For individuals with transradial or transhumeral amputation, this would influence the loading of the residual limb muscles situated in the prosthetic socket from which the EMG signals are recorded. Also, different limb positions may induce varying level of gravitational force, thus leading to displacement of the target muscles. These factor would normally cause alterations in the EMG signal patterns due to the compression of the muscles and, possibly, elicitation of mechanical stimulation or eccentric contraction of the muscles. And such alterations in EMG signal patterns would undoubtedly affect the performance of EMG-PR based prosthesis control.

Towards resolving the effect of variation in limb positions on the performance of EMG-PR based system, Geng *et al.* [82] conducted an experiment involving five

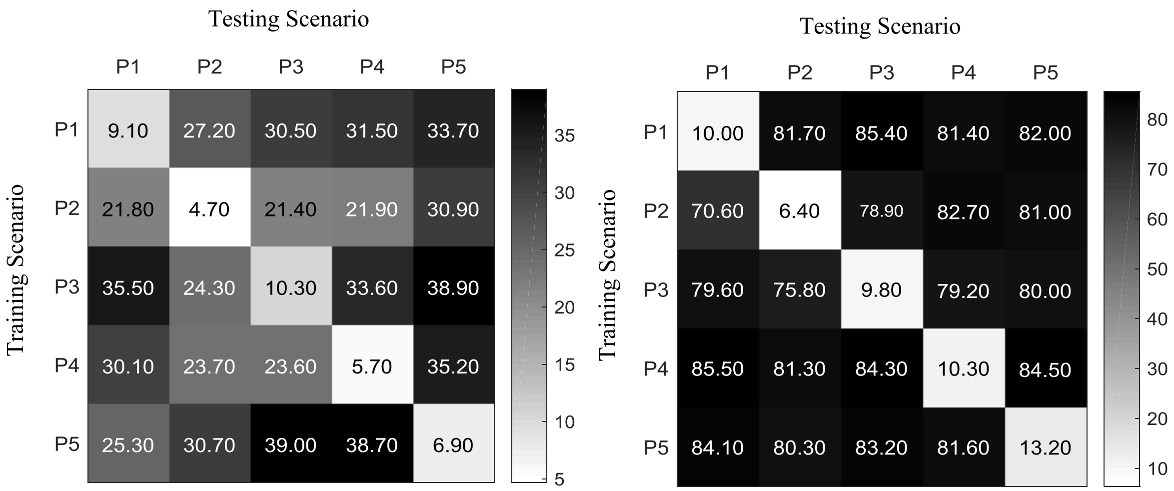

FIGURE 7. Experimental results of limb motion intent prediction. (a) Using EMG data as the classifier's input. (b) Using ACC-MMG data as the classifier's input.

amputees whose post-amputation periods varied from 2∼10 years and had residual forearm lengths ranging from 5cm∼14cm. The amputees have experience in the use of either a myoelectric or cosmetic prosthetic arm in their daily life, making the experiments relatively easier for them. The experiments involved simultaneous acquisition of EMG and ACCmmg signals corresponding to seven classes of limb motions (hand close and open, wrist supination, pronation, flexion, and extension, and no movement) in five different limb positions. The recorded signals were firstly preprocessed, then Hudgin's time-domain features and LDA classifier were considered for the analysis. The obtained results (Fig. 7) demonstrates that when data for a particular limb motion say "wrist flexion" obtained from limb position P1 is used to train the classifier and the trained classifier is tested with wrist flexion data obtained from other limb positions (P2, P3, P4, or P5), the CE for that motion increased significantly (the off-diagonal entries).

However, when the data used for training and testing the classifier comes from the same limb position, the CE decreased significantly (the diagonal entries of the matrix), suggesting that variation in limb positions while eliciting targeted limb motions would greatly degrade the performance of EMG-PR based controlled prostheses. In an attempt to address the degradation caused by variation in limb positions, different training strategies have been suggested [82]. Most of the strategies basically considered including possible representative samples into the training set so as to increase the chance of achieving high and consistent accuracies for limb motion intent decoding. Meanwhile, other possible solution would involve the use of additional signal source such as the ACCmmg to predict the limb position per time before utilizing EMG to classify the limb motion.

In this regard, Geng *et al.* [82] built several classifier models based on LDA algorithm that were trained using EMG data from multiple arm positions (P1-P5) and subsequently tested using EMG data from all five arm positions. A total of 31 motion classifiers (consisting of 26 multiple position classifiers and 5 single position classifier) were built. Generally speaking, the error gradually decreased along with more arm positions included in the classifier training. When the EMG data from all five arm positions were involved in the training set, the average classification error reached a minimum value of around 10.8% for the amputated arm and 10.3% for the intact limbs. Note that in most of the 31 motion classifiers, the amputated arms had a low classification error, in comparison with the intact limbs [82].

D. ELECTRODE SHIFT DURING DONNING

In the practical use of a prosthesis, the EMG electrodes may assume slightly different position relative to the underlying musculature each time the device is donned. The electrodes may also shift during usage as a result of loading and positioning of the amputee's residual limb. Such shift in electrode positions may lead to alteration in the characteristics of EMG recordings for the limb movements over time, thus making it difficult to decode the movement. For example, a shift of approximately 1cm of four surface EMG electrodes around the forearm circumference of an individual increased classification error in a 10 class motion recognition problem from about 5% ∼ 20% (if shifted distally) and to about 40% (if rotated about the forearm) [83]. In addition, the inclusion of shifted versions of the EMG recording into the training session has been shown to virtually eliminate degradation due to shift in the test set [59], [83]. A different approach examining the influence of bipolar electrode configurations, revealed that electrodes with larger surfaces that are widely spaced could improve resilience to shift but not nearly as much as incorporating exemplars of shift into the training set [84].

Shifting of electrode position would normally occur during day to day session when the prostheses is being donned. And the EMG recordings corresponding to each donning can then be stored and reused to model the pooling of data from various shift locations. With the accumulation of data from all the possible shift positions, the system may become robust to typical shifts encountered for during donning and in practical use. Thus, a daily calibration is probably warranted to accommodate other influences that may affect the EMG, such as electrode impedance (due to skin dryness, humidity) and learning effects as the amputee become more experienced. Electrode shift do not only affect the signal quality of EMG recordings but also that of ECG recordings [85]–[87], and other physiological signals.

IV. FUTURE PROSPECTS OF EMG-PR BASED PROSTHESES CONTROL

The overall performance of multiple DOF upper-limb prostheses driven by EMG-PR control method could be improved to meet the long expected desires of its potential users by exploring the following perspectives with respect to the existing challenges. For instance, transient changes in EMG signals arising from short and long-term variations in the acquisition environment during practical use have been shown to degrade the clinical robustness of device, and thus limit its adoption by users. These transient changes often result from external interferences, electrode impedance changes, muscle fatigue, and electrode shift among others. One possible way to handle these issues would be to consider developing intelligently driven strategic filtering and electromagnetic shielding techniques that could attenuate or even eliminate most of the interferences.

Another major limitation of the existing EMG-PR based prostheses is that they do not support continues classification which makes them different from the natural control phenomenon. Realizing simultaneous and proportional articulations of multiple DOFs movements associated with the natural limb becomes a big issue with the currently available EMG-PR based prosthetic control schemes. In this regard, a number of researchers conducted studies on developing prostheses control methods that could provide simultaneous and proportional control of multiple DOFs joint movements to realize more intuitive and advanced control of artificial limbs [70]–[72]. However, the real-life implementation of this concept is still a challenge till date.

Sources of variation in EMG signals that are intrinsic in nature, cannot be effectively suppressed and they are even more challenging to resolve. Even if the EMG-PR based prosthetic system is calibrated upon donning, the nature of the effects of such variation is unpredictable, therefore, the system would need to adapt to the changes in EMG signals. Meanwhile, adaptive EMG-PR method for multiple DOF prosthesis control has been rarely studied to date [88]–[90]. One possible reason is that, the adaptation of an intelligent pattern classifier is challenging since the system needs to know exactly how and when to adapt. Such intelligent pattern recognition system should be able to learn and know how to adapt properly to the intended limb movement based on prior knowledge from generated data. Meanwhile, in cases where the amputees are instructed (supervised) during the data acquisition, the limb motion classes are obviously known and the recognition task becomes a straightforward one for the classifier. On the contrary, the core benefits of the adaptive pattern classifier are, during normal unsupervised use, in which the system needs to accurately predict the intended class. Also, knowing when to adapt is equally crucial. For instance, when parsing a data stream in real-time, the EMG-PR system should be confident that the data are representative of the estimated class. In this regard, such intelligent adaptive prosthetic system might meet the expectations of most of its users and thus increase the adoption of the device for usage in their daily life. Towards making this a reality, the COAPT engineering, a company based in Chicago recently developed a commercially available, intuitive EMG-PR based control for advanced prosthetic arms [91].

Rather than relying on the use of the already proposed training strategies that are found to be limited in a number of ways, developing an intelligently adaptive pattern recognition based controller could go a long way to resolve the discrepancy in EMG signal patterns for the same limb movement resulting from variation in muscle contraction force, changes in limb positions, and subject mobility as discussed in the previous sections. This is because improvement as a result of adaptation has been reported during extensive use of a prosthesis particularly in the presence of electrode shift and muscle fatigue [83], [84]. However, proper understanding of the dynamism of such adaptive concept and how it interact with users of the prosthetic device are lacking to date. By further exploring such an adaptive concept, a fully stable, unsupervised method that could be of great clinical interest can be realized. Therefore, an open research area would be to fully explore such an adaptive concept in respect of the confounding factors affecting the clinical robustness of the currently available multiple DOF prostheses, and also to develop an intelligently driven unsupervised pattern recognition based control solution.

In light of the advancement in the field of sensor technology, developing sensors that could capture muscle spatial information associated with changes in muscle shape could provide useful and stable information from which limb movement intent can be decoded. Such muscle shape change information can serve as useful input to pattern recognition based control system instead of the traditionally utilized EMG signals, because the corresponding impedance signals from such sensors can be obtained at lower sampling rate (typically 125 Hz) in comparison to that of the commonly utilized EMG sensors (1000Hz$\sim$2000Hz) [16], [17]. This low sampling rate would lead to less computational burden, and this could be another possible research direction in the field of upper limb rehabilitation technology.

The concept of adopting deep learning in pattern recognition based prostheses control is currently being explored by several research groups around the world. This is because, the deep learning has the potential to address the problem of feature extraction that represent the core of the conventional

EMG-PR based prostheses control system [92], [93]. At the moment, the use of deep learning concept has rarely been applied to providing simultaneous and proportional control schemes for multiple DOFs prostheses. Hence, there is need to conduct more research in this direction. Also, with the advancement in hardware development for multi-channel surface electrodes, the use of high-density sEMG arrays could be a promising approach in future especially when explored using deep learning.

V. CONCLUSION

Though the potentials of intelligent pattern recognition based control methods for multiple DOF upper-limb prostheses have been well investigated but their clinical robustness are currently being challenged by a number of confounding factors. Towards facilitation the clinical realization and improve the acceptance rate of multiple DOF prostheses, this paper explored the dynamics of the core aspects of intelligently driven prosthetic control methods with emphases on EMG-PR approach. And it was found that by applying an optimized machine learning scheme, substantial degradation in performance of the traditional EMG-PR methods of about 17.0% and 8.98% resulting from variation in muscle contraction force and subject mobility, could be meaningfully reduced. Considering the advancement in intelligent computing algorithms, there is higher chance that the near future will be a transitional period for EMG controlled systems that would provide more functional benefit to upper-limb amputees.

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