Selection of Features and Classifiers for EMG-EEG-Based Upper Limb Assistive Devices—A Review

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(Methodological Review)

***Abstract*—Bio-signals are distinctive factors in the design of human-machine interface, essentially useful for prosthesis, orthosis, and exoskeletons. Despite the progress in the analysis of pattern recognition based devices; the acceptance of these devices is still questionable. One reason is the lack of information to identify the possible combinations of features and classifiers. Besides; there is also a need for optimal selection of various sensors for sensations such as touch, force, texture, along with EMGs/EEGs. This article reviews the two bio-signal techniques, named as electromyography and electroencephalography. The details of the features and the classifiers used in the data processing for upper limb assist devices are summarised here. Various features and their sets are surveyed and different classifiers for feature sets are discussed on the basis of the classification rate. The review was carried out on the basis of the last 10–12 years of published research in this area. This article also outlines the influence of modality of EMGs and EEGs with other sensors on classifications. Also, other bio-signals used in upper limb devices and future aspects are considered.**

***Index Terms*—Electromyography, electroencephalography, pattern recognition.**

I. Introduction

The human-machine interface involves the use of human signals to decode intentions and use them to control electronic devices [1]. One of the ways to design an interface is to use the electrical activities originating from human body. These electrical activities usually acquired from the brain or muscles are detected by techniques called electroencephalography (EEG) and electromyography (EMG); respectively. These signal based interfaces find their appilcation in the design of assistive devices such as prostheses and orthoses.

Inevitable adversities such as accidents or wars are major causes of amputation, followed by amputations due to diseases like diabetes. The recent data depicts more than 1 million amputation are taking place every year [2]. It is estimated that about 5,000 new upper limb cases are added each year in India. The statistics on human limb amputation in US shows an increament in its rate since 2009; leading being diabeties [3]. The most common upper upper limb amputation is finger amputation. Recent advances have realized the need for rehabilitative or orthotic devices as well. The orthotic devices find their applications to perform complete and precise motions after disabilities. The disabilities can be due to limb numbness; post-stroke rehabilitation [4]; parkinson [5] etc.

Now-a-days; upper limb devices such as Michelangelo Hand, Smart Hand, bebionic hand are available in the market [6], [7]. The development of tiny and lighter components has resulted in more practical devices. Still; surveys have shown denial of existing prosthetic devices in the market. The reasons are irregular classifications of action, higher cost, heavy weight and difficult to use [8].

From designing perspective; the control schemes of EMG based assistive devices can be designed by on/off, proportional or pattern recognition techniques. Among all, the pattern recognition based control systems are most preferred and effective. The pattern recognition based devices are capable to focus on large premise of action based on EMGs or EEGs. The advantage of the pattern recognition based control schemes lies capacity to work with the continuous and precise tide of information to mimic complete limb motion encompassing reaching, grasping, applying optimal force, lifting up, placing and resting of hand. This results in need for more synergized data; sharp signal processing; strong control schemes and high quality hardwares.

The various reviews published in this area have addressed various aspects related to pattern recognition based devices. A significant effort has been made by researchers on the pattern recognition based control strategies for orthosis and prosthetic devices. Phinyomark *et al.* [9] discussed some feature strategies in literature explaining about various features. Samuel *et al.* briefly discussed about the different steps followed in the EMG-pattern recognition technique [10]. Besides; the author also addressed issues like effect of mobility; effect of muscle variation and effect of limb position. L. Bi *et al.* also reviewed the EMG based human-robot interaction for continous upper limb motions. However; they focused on the design of the regression control model in contrast to the review of biosignal signal processing performed in this review [11]. Few recent reviews are listed in Table I. Although previous reviews discussed the

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TABLE I
LIST OF PREVIOUS REVIEWS DONE RELATED TO BIO-SIGNAL PROCESSING AND CLASSIFICATION

Study	What was incorporated?
Fang et al. [12]	EMGs: Electrode Positions, Subject Selections; SMGs, MMGs ENGs; BMIs: EEGs, ECoGs; Multi-Modality
Phinyomark et al. [9]	EMGs: feature extraction
Rechy-Ramirez et al. [13]	EMGs: data acquisition, feature extraction; EEGs: feature extraction; Classifications
Lotte et al. [14], [15]	Classifications methodologies for EEGs
Ison et al. [16]	EMGs: Electrode Positions, Subject Selections; Feature Extraction; Pattern recognition: Classifications; Motor learning based control schemes
Spiewak et al. [17]	Features of EMGs and classifiers
Geethanjali [18]	Control Schemes; Pattern Recognition

SMGs: Sonomyography, ENGs: Electroneurography, BMIs: Brain-Machine Interfaces, ECoGs: electrocorticography; MMGs: mechanomyography.

applications of different feature sets; no previous reviews to our knowledge has investigated the corelative use of various feature sets and classifiers. Unlike previous reviews; the conclusions are drawn to identify feature/feature set-classifier combinations based on previous studies.

This review largely incorporates recognition studies of upper limb models over the last 10 years; to incorporate latest reasearches. It was noted that during this period extensive exploration in this domain was performed. However; Certain research papers before 2008 referred in recent papers were also used to design this review. The literature search was carried out using databases like IEEE Xplore; Science-Direct; Scopus; MDPI etc.. The search and sorting of the reseach documents was done by using keywords named as upper limb, Elecromyography, electroencephalography, assistive devices, pattern recognition classification etc. Further; the selected literatures were divided into three groups according to the purpose of the study: feature extraction; classification and multi-modality. In this study, the various features and their sets; along with classifiers are studied and their usability is evaluated based on the their classification results and repeatable usage in different studies.

The following section “Review” details EMG and EEG techniques for electrical signal analysis and its various aspects involved in the design of upper limb assistive devices. Further; the effect of modality on classification are also discussed in this review. Sections III, IV, and V present concluding remarks and future expectations from the literature review under Discussion, Future aspects, and Conclusion, respectively.

II. REVIEW

A human body is the result of various body segments in the form of bones, muscles ligaments and tendons fused with various sensing capabilities to procure an amalgamated interfacing to perform activities of daily living. The sensing capabilities are in various forms such as electrical activities in muscles; magnetic fields in heart; vibrations at body joints and thousands of mechanoreceptors on skins. The electrical activities originate from the human brain, travel to various body parts with muscles cells as the carriers. Electroencephalography is used to extract electrical activities from the brain whereas the skeletal muscle activities are monitored by EMGs. The challenge with these signals lies in the likelihood to extract useful, continuous and noise free information. To obtain such information; the data is passed through various data processing techniques divided into signal conditioning, feature extraction and feature set formation as shown in Fig. 1. The following Sections II-A and II-B largely elaborates about these two electrical-activity based measuring techniques. Further; other additional techniques; effectively used for better interpretation in upper limbs like MMG, SMGs etc. are also discussed.

A. Electromyography

An EMG based assistive system is designed by using the information incurred from the active skeletal muscles. Their pattern recognition based control systems comprises of signal processing and the classification of electrical signals retrieved from the muscles as shown in Fig. 1. The processing of data involves 3 main aspects named as data segmentation, features extraction and features sets.

1) Data Segmentation: The segmentation ensures continuous distribution of the information to allow simultaneous classification and actuation at a particular time. The data segmentation is performed by two techniques: overlapping segmentation and disjoint segmentation.

Disjoint segmentation divides into separate segments with a predefined length [17]. In overlapped segmentation, a new segment incorporates a part of the earlier segment. The overlapped segmentation is largely dependent on two factors: segment length; and increment [13], [17].

Most researchers prefer to implement overlapped segmentation for upper limb analysis. Oskoei and Hu Zhang *et al.* analyzed pattern recognition for the control of hand movement applied overlapped analysis. The segment length, used was 256 ms and a window increment of 32 ms [19]. Another researcher, Ali H. Al-Timemy divided electrical signals of EMG into overlapping windows of 200 ms and 150 ms with an increment of 50 ms for classification of finger movements in two studies.[20], [21].

The reason for using overlapped segmentation technique is because of a more consistent controller output delay. As a result, the maximum delay produced by the controller is decreased as well [20]. The output sent by a controller dependent on factors such as length of analysis window and the signal processing time. The windowing time appropriate for such performance is estimated to be between 150–250 ms with an increment of around 50 ms [22]. Thus, with the availability of resources to process for high computation, it is pertinent to apprehend an overlapped segmentation technique.

2) Feature Extraction: The objective of feature extraction is to obtain appropriate data information from the raw EMG signals. The selected features are also dependent and/or related to the selection of a control scheme accordingly [16], [23], [24]. The performance of myoelectric devices is highly dependent on the selection of features. Broadly; the feature extraction techniques are divided into three domains: time domain; frequency domain; and time-frequency domain techniques.

a) Time Domain Features: The main advantage of using time domain features is the ease of calculation, without requiring much mathematical computation. Thus; the time domain features are more commonly used for upper limb pattern recognition techniques. The computation of time domain

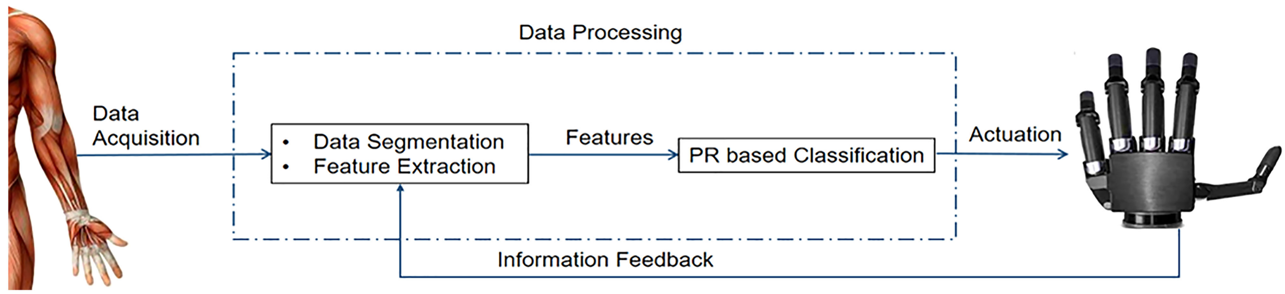

Fig. 1. Sketch showing the steps involved to perform motion using EMG based controlled devices.

features is based upon signal amplitude [17]. These features also find applications in developing relationship between muscle contraction level and force. Some of them are integrated EMG (iEMG), Mean Absolute Value (MAV), modified mean absolute value (MMAV), simple square Integral (SSI), Root Mean Square (RMS), and Waveform Length (WL) etc. A few time domain signals such as zero crossing (ZC) and slope sign change (SSC) are closely related to a measure of frequency domain features [16]. Based on utility in upper limbs, iEMG, MAV, RMS, and WL are more effectively used individually compared to rest of time domain features.

Integrated EMG; viz the summation of absolute values of EMG signal amplitudes over a segment, is very often used in the detecting properties pertaining to hand prosthetics [25]. The advantages associated with iEMG are ease of extraction and consistent rather than the best results [26].

Mean Absolute Value is defined as the average of the sum of absolute amplitudes [9], [27]. The comparison of MAV with other features depicts a variegated behavior for identifying various grasping gestures in upper limb prosthetics. Wu *et al.* [28] selected four predominantly used time domain features for exploration of grip force: MAV; variance (VAR); ZC; and WAMP. These were compared on the basis of mean absolute value error and root mean error [28]. Jochumsen *et al.* selected MAV, WL, ZC and SSC to investigate the role of arm position for the inter-class classification accuracy of five motion classes. The classification tendency was found highest when MAV and WL were used as features [29].

Root mean square is essentially used for force and fatiguing contraction estimation [30]. The RMS feature is extensively used for classification of gestures, force estimation during grasping [31], within hand-lifting at different loads [32] and fatigue estimation [33]. It performs well where force estimation is required, while grasping. In a study by Kamavuako, RMS and WAMP showed the best performance in comparison to MAV, SSC, ZC, modified mean absolute value (MMAV), Constraint Sample Entropy (CSE), and EMG envelope (EMGenv) [34]. The performance of RMS is found to be better than SSC and ZC features [34]. Another study by Phinyomark *et al.* showed RMS performed better compared to MAV, iEMG, VAR, SSI, ZC, SSC, MMAV, mean frequency (MNF) and autoregressive coefficient (AR) [35].

Waveform Length is another significant time-domain feature. It is defined as the aggregated length of the waveform over the segment. Very often, the classification performance of waveform length is quite high compared to the rest of the features as discussed above [29], [34], [36]. Like RMS; WL is used in the tasks of hand grasping, force estimation and hand gesture. One such study was done by Phinyomark *et al.*, where hand movements using conventional time and frequency domain features were evaluated. In this study, WL was found to be optimal among 15 features extracted using RES index and SVM classifier [35].

Simple square integral (SSI) (also called Integral Square) and Variance of EMG incorporates energy of the EMG signal for feature extraction [9], [37]. Time domain features like ZC, SSC, WAMP and Myopulse percentage rate (MYOP) are time domain features which are actually a degree of frequency domain features. The classification accuracy of these signals is usually lower as compared to time domain features discussed earlier [27], [38]. These signals are rarely used as individuals for feature extraction. The main applications of ZC and SSC come in feature sets. The earliest use of these features was done by Hudgins in 1993, in which he formed a feature set of MAV, ZC, SSC and WL [39]. Willison Amplitude has found its application more than other frequency based time-domain features. The classification accuracy of WAMP was found higher as compared RMS and AR. In the same study, WAMP performed poorer than RMS and AR with Linear Discriminant Analysis (LDA) classification [38]. However, Negi *et al.* found WAMP as an optimal feature for limb movements using LDA classification technique [36]. Thus, no conclusive results can be drawn about individual performance of WAMP feature.

Phinyomark *et al.* proposed six time-domain features in the study. These were mean absolute value slope (MAVS), multiple hamming windows (MHW), Histogram of EMG, Multiple trapezoidal windows, autoregressive (AR) coefficients and cepstrum coefficient (CC) [9]. Among them; the most frequently used extraction technique is the AR coefficient [9]. It has been effectively used in pattern recognition techniques for hand gestures and force estimation. AR coefficient picks each sample of the EMG signal as a linear combination of the previous sample plus a white noise error term. This is very often used in addition to time domain features in a feature sets [16], [23]. Another similar feature is cepstrum coefficient (CC). Phinyomark *et al.* grouped AR and CC as time domain modeling feature group [40]. Few lesser known time domain features are used in upper limb prosthetics like log detector (LD), kurtosis(KUR) and skewness (SKW) but their classification performance was comparatively lower [41], [42].

b) Frequency Domain Features: Frequency domain (FD) features are usually applied to estimate muscular fatigue [43], [44] and force prediction [45]. Frequency Domain features are disadvantageous due to computational complexity which results in spectral leakage and high variance [16]. Phinyomark *et al.* mentioned about 12 frequency features, describing power spectral density (PSD) as an important analysis tool. The other features are obtained by applying mathematical

TABLE II
ADVANTAGES AND DISADVANTAGES OF DIFFERENT FEATURES OF EMGS

Feature	Features Names	Significance
Time Domain Features	iEMG; MAV; MMAV; RMS; SSI; VAR, LD; WL; ZC; Average Amplitude Change (AAC); WAMP; SSC; MAVS; MHW; AR; CC; KUR; SKW; ASS	Advantages: • Simple to Compute • Quick • More often used in force-EMG relations Disadvantages: • Noise sensitive
Frequency Domain Features	MNF; MdF; Power Spectrum (PS); Mean Power (MP); SM[k]; Frequency Ratio (FR); PSD; Peak Frequency (PF)	Advantages: • More often used in fatigue estimation Disadvantages: • Computationally Complex • Information loss due to spectral Leakage
Time-Frequency Features	Wavelet transform; short-time Fourier transform; "Cohen Class", S-transform and BD.	Advantages: • Regarded best for information extraction. • High dimensional output Disadvantages: • Computationally expensive

analysis to PSD. Power Spectral Density is defined as the rate with which the motor units are fired [9].

In upper limb prosthetics, power spectrum (total power), mean frequency (MNF), median frequency (MdF) and spectral moments(SM[k]) are more frequently applied. The features such as MNF, MdF and power spectrum are based on PSD. The spectral moments are lesser explored methods to extract features from PSD. A recent study by Savithri *et al.* [46] showed that the three spectral moments had a higher correlation value compared to other frequency domain features. Among these moments, the 3rd order spectral moment resulted in a more effective feature in the frequency domain [46]. The frequency domain features results in lesser prominance of class separability and is demarcated as a disadvantage of these features in comparison to the time domain features [35], [47]. The advantages and disadvantages of all feature types are mentioned in Table II. Phinyomark *et al.* suggested modifications to mean frequency and median frequency to improve their performance of feature extraction by removing white Gaussian noise (WGN). Two frequency domain features were named as "Modified mean frequency" (MMNF) and "Modified median Frequency" (MMDF), where earlier feature showed better robustness of EMG features [48]. Other lesser-known frequency features are derived by using short time Thompson transform (StTT) [37] and spectral magnitude average [16], [37]. Many authors prefer to categorize short time Fourier transform as time-frequency features. Therefore, these combination of features are discussed in the next section.

c) Time-Frequency Features: Time-Frequency Features incorporate both time and frequency characteristics of signals, thus showing improved pattern for dynamic contraction. The significance of time-frequency features is their capability to involve non-stationary signals. This results in an increase in the recognition rate of the system. The most prevalent time-frequency features are wavelet transform and short-time Fourier transform [27], [49]. Other feature methods include "Cohen Class", Stockwell-transform (S-transform) and B-distribution (BD) [33]. These features are more used in muscle fatigue estimation [33]. The Cohen class includes the spectrogram, Wigner Distribution (WD), Reduced Interference Distribution (RID) and Margenau- Hill distribution [50]. The applications of these tools were not found in the control strategies methodologies for prosthetic devices.

Presently; the wavelet transform and wavelet packet transform are important for time frequency features[24], [51]. The advantage associated with wavelet transform analysis is its capacity to perform concurrent analysis of the local features of a non-stationary signal in both time and frequency domain [52]. It is viewed as an improvement to windowed Fourier Transform. The wavelet transform is applied in two forms: a discrete wavelet transform (DWT) and a continuous wavelet transform (CWT). The DWT technique transforms the signal of the interest into multiple resolution subsets of coefficients; as a result, it takes more processing time [53]. However, DWT turns out to be a more consistent and efficient technique as compared to CWT [24], [53]. The applications of wavelet transform are found in gripping forces estimation and hand gestures of upper limb prosthetic devices. For instance, Kai Wang *et al.* developed a wavelet scale selection technology to accurately generate handgrip force from sEMG during a force-varying muscle contraction using wavelet technique [54]. Soo *et al.* also investigated the role of wavelet transform and developed a stable and precise predictor of handgrip force from EMG [55]. Savithri el al. also incorporated DWT. The RMS, MAV and WL are extracted from 4th level approximation coefficients to investigate the EMG activities of left and right arm. The wavelet transform is essentially applicable in its utility along with time domain features to improve the recognition rate of a system [56]. However; the time-frequency features are computationally complex leading to higher costs and a longer time [50].

Apart from it, few researchers suggested novel time-domain features. Samuel *et al.* proposed 3 novel time-domain features. These were Absolute Value of the Summation of square root (ASS), Mean value of Square Root (MSR), Absolute value of the Summation of the nth root of the data in a given analysis and its Mean (ASM). These signals were subjected to full-wave rectification to ensure mathematical computation. These features were compared with 7 conventional time-domain features mentioned in Table IV. The basis of comparison of the features was the classification of actions using ANN and LDA. The novel time domain features, ASS, ASM and MSR resulted in better performance as compared to most of the conventional features. [38]. Al-Timemy *et al.* also proposed new features to improve force variation detection for prosthetic devices. The proposed features were named as Sparseness, Irregularity Factor (IF) [31] and Waveform Length Ratio (WLR) [1], [20]. Other recently proposed time domain features include difference absolute mean value (DAMV), difference variance value (DVARV) and L-scale (LS) [40], [41].

3) Feature Selection and Sets: Feature extraction of various time, frequency and time-frequency domain features results in a multi-dimensional vector system. Performing analysis on all features results in high computational complexity, cost and time. Among these features, few features are redundant and can be removed. This is done by a technique called "Feature Selection", which results in different feature groups or combinations. Feature selection forms a miscellaneous group of features from different feature domains. This helps to perform pattern recognition in reduced time and optimal results are obtained by computing lower prefixed data.

A feature set of MAV, SSC, ZC and WL was sugggested as a novel feature set by Bernard Hudgin *et al.* in 1993 [39]. This feature set is still largely used in researches and is called as "Hudgins set" or "Time-domain set" (TD) [18], [25], [27], [58]. The feature set selection depends on factors such as the tasks, different classification methodologies and statistical methodologies. The Table IV shows different feature sets employed for different pattern recognition experimentations. Feature Selection involves reduction of dimensions and removing unwanted features. This can be done by techniques such as Davies-Bouldin, genetic algorithm, Kohonen's self-organizing map, particle swarm optimization etc. [18]. Different researcher used different selection technique for selection of feature combinations to optimally achieve task efficency. In certain studies; the forming of a feature set is based on permutations and combinations of different time domain, frequency domain and time-frequency domain features [58]. For instance; Al-Timemy *et al.* investigated the classification of finger movement for hand prosthetic control using TD-AR features. Altogether; 11 features were extracted from each EMG channel, thus resulting in a high dimensional vector. TD-AR features involved the coefficient of a 6th-order AR model, RMS, WL, ZC, integral absolute value (IAV) and SSC [21]. To shorten this feature vector, two feature reduction techniques were employed, namely principal component analysis and orthogonal fuzzy neighborhood discriminant analysis.

B. Electroencephalography

Electroencephalography is a technique to obtain electrical neural activities from the human brain, effectively applicable for the brain-computer interface (BCI). A brain-computer interface (BCI) translates the brain activity patterns of a user into action [59]. EEG based BCIs find their applications to control assistive and prosthetic devices, for example, wheelchairs, rehabilitative devices for stroke patients or cerebral palsy etc. Unlike EMGs, the applications of EEGs in the design of assistive devices are limited. The researches have been devoted to decoding different hand grasping approaches while acquiring information from a complex network involving the frontoparietal region [60]. The analyses required for EEG processing are briefly discussed in the following sections.

1) Data Processing: Like EMGs, EEG signals undergo processing for feature extraction, feature projection and classification to achieve use of BCI as a prosthetic control system. The general data segmentation techniques are based on the findings of Kaplan *et al.* [13]. They divided data segmentation approaches into two: fixed-interval segmentation; and adaptive segmentation [13]. Many researchers cited data segmentation technique as suggested by Wang *et al.* and Biscay *et al.* [61], [62]. There are few properties of EEG features, which make them difficult to work on. EEG based features are noisy, resulting in low signal-to-noise ratio. Also, signals extracted from several channels form a high dimensional feature vector. Lastly; the signals vary too rapidly over time as compared to EMG based electrical activity [15].

A variety of features have been used to design BCI for upper limb assisitve devices. Few examples of such features are band powers (BP), power spectral density (PSD) values, autoregressive parameters etc. Largely, the feature extraction techniques are categorized as band power features (spectral features), temporal features and spatial features [13], [63]. Band Power values are based on the energy of EEG activity reflected in several frequency bands [13]. These features represent identical information to the frequency domain features of EMGs. Few examples of frequency based features are autoregressive coefficients, power spectrum etc. Popular EEG based interfaces working on frequency activity are motor-imagery based BCI, [64] steady-state visual evoked potentials (SSVEP)-based BCI [65] and BCI based on cognitive imagery tasks.

Time domain features are derived from the signal and are a result of the concatenation of EEG samples from all channels. They are mostly used for Event-Related Potentials. One such method of event-related potential popular among researchers is P300 BCI [66]. This allows improving decision making at a particular instant as wished by subjects. P300 technique is defined as the largest positive deflection that occurs around 300 milliseconds after the stimulus onset. The time domain features which are more often extracted are: mean value, standard deviation, maximum peak value, kurtosis etc. [13]. Time-frequency domain represents the spectrum variation over time. Time-frequency features mostly employed in upper limb analysis are short time Fourier features and Wavelet transform. Spatial features are special class of features which describes a spatial origin of the signal. This results in more focus on signals originating from a specific site of the brain [63]. This is also regarded as the spatial filtering of signals [13]. In most cases, time domain and frequency domain features are extracted after spatial filtering.

Feature selection plays a pivotal role in harnessing an optimal set of features. Various feature selection techniques may include genetic algorithm, [67] principal component analysis [68], [69] LDA [68] etc. The algorithms applied for pattern recognition using EEGs are similar to EMGs. However, the average accuracies from the pattern recognition technique for the upper limb have shown motivating results but need further efforts. A few recent research documents related to BCIs for upper limb are tabulated in Table V.

C. Other Bio-Signals Based Systems

Certain human signal sensing techniques such as SMGs, MMGs and ENGs can be used for designing upper limb assistive devices. Sonomyography involves the application of ultrasonic imaging which has an advantage of detecting different muscles enveloped inside within superficial layers [70]. One such study involved the use of ultrasonic systems to determine the changes in wrist angle for any change in muscle thickness signal [71]. Sikdar *et al.* also designed an ultrasonic imaging based control strategy for the classification of finger movements [72].

Mechanomyography can also be used as an alternative to electromyography, in certain situations. Owing to its characteristic of having a higher signal-to-noise ratio; such sensing technique is capable to detect muscle activity from deeper muscles. Wilson *et al.* used a MMG based control system for gesture recognition, with a classification of 83.5% [73]. Recent work on MMGs has suggested a fusion of MMGs and EMGs to improve maneuvered actions of the control system [74].

Targeted Muscle Reinnervation (TMR) involves a surgical method to improve the controlling of upper limb prosthetic by recreating muscle recording sites which were lost after amputation [75]. Hargrove *et al.* employed TMR with pattern recognition and compared with direct EMG based control system. After a 6–8 weeks of data collection; the earlier control system performed better on the basis of statistical assessment tools [76].

TABLE III
ADVANTAGES AND DISADVANTAGES OF DIFFERENT CLASSIFIERS

Name	Advantage	Disadvantage
NN [16,23]	• Non-linear capability • Adaptability • Better for large database • Easier Input/output mapping	• No common solution • Overfitting • Slow training
SVM [23,24, 131]	• Lesser complicated; • Non-Linear Capabilities • Robustness	• No Dual Association
LDA [13], [15]	• Easy to Use; • More reliable for lesser database.	• Linear Capabilities • No Dual Association
RF [21]	• Flexible & high accuracy • Processes well irrespective of dataset count.	• Time consuming • Complex

III. CLASSIFICATION OF BIO SIGNALS

Classification identifies various categories of feature information to assign respective actuation in the system. The actuation is a result of identification in the form of discrete labels derived from a group of features extracted. In regards of pattern recognition, the process of classification is performed by schemes such as LDA, [30], [36], [77] Support Vector Machines (SVM) [78], neural network (NN) [80], fuzzy logic (FL) [81], [82] etc.. The robustness of a control system designed using such schemes is dependent on training of the data set with desired outputs and. effectively implementing them in myoelectric assistive devices. The classification schemes are broadly classified as linear and non-linear classification algorithms. Linear classifiers are more often used in real-time control systems due to their ease in computation. However, linear classifiers fail to perform better for complex systems. Such schemes often fail to integrate the interactive and non-linear behavior of muscle system with the machine. The controlling system designed using non-linear classifiers are readily capable to extract non-linear behavior of EMG and desired output. Their application is also prevalent in the multi-modal analysis required for upper limb control systems [83], [84]. The non-linear analysis leads to higher processing time and requires repeated training to avoid over fitting [31], [83]–[85].

Regression schemes are pattern recognition based control system used to predict extended outputs after training and learning a set of data sets [31], [86]. These schemes are used in continuous and adaptive motion of systems. There has been a surge towards regression schemes because of its capability to extend its controllability beyond certain sets of control points. The selection of classifier may depend on factors such as level of complexity, types of features extracted and computational time required to perform a given action. The level of complexity varies on the basis of number of the muscles selected and kinematic and dynamic parameters. The advantages and disadvantages of different classifiers is listed in Table III.

A. Linear Discriminant Analysis

Linear Discriminant Analysis is the most commonly used linear classification scheme for pattern recognition of upper limb action. Apart from classification, LDA is also used for feature reduction. Another advantage associated with LDA is its fast computation. The LDA employs hyperplanes for the differentiation of data points into various classes. Such schemes were used for supervised classification of the feature vectors. The most frequent LDA method is "Fishers linear discriminant Analysis". Additional changes have been implemented into LDA to improve pattern recognition techniques; for example quadratic discriminant analysis [30]. The classification performance using LDA for various time domain features tends to vary around 80-90%, thus undermining the chance of overfitting [38]. However, many studies have used LDA to compare with non-linear classification tools as shown in Table VI. Thus; most often suggesting a lower recognition rate compared to other techniques [21], [87].

B. Naïve-Bayes Classifier

This classifier works on the principle of Bayes classification and Bayes theorem [78]. The classification rate is usually lesser compared to other linear and non-linear classifiers [33]. The only pronounced advantage is its lower processing time. Its applications in previous researchers are very limited [78]. Al-Timemy *et al.* used Naïve- Bayes as one of the classifier to investigate control of EMG based system against different level of forces. For given feature sets; the error rate by Naïve-Bayes algorithm was highest as compared to LDA and RF. However; time period of the classification significantly lower in comparison to RF and k-NN [20].

C. Support Vector Machines

Support vector machines are the most used classifier for pattern recognition control of EMGs and EEGs. SVM has found its application in hand gesture recognition [87], finger gesture recognition [88] and force estimation [31], [89]. The results using SVM estimated higher recognition rate than linear classifiers. However, comparative studies of SVM with non-linear classifier suggest mixed conclusions. In many cases, SVM performed better than non-linear classifiers such as k-NN but failed to detect higher classification in comparison with complex neural network techniques.

The idea of SVM was to identify a hyperplane which has a maximum distance from all classes. SVM is used as a non-linear classifier by employing a kernel-based algorithm. The kernel-based SVM variants have been enormously explored, proposed and put into practice [88], [90], [91]. Few of the frequently used SVM based algorithms for upper limb analysis are least-square SVM, SVM with linear kernel and SVM with RBF kernel [87]. In general; the classification rate using SVM is greater than 80% [92], [93].

D. Neural Network

Neural networking classification is a much flexible non-linear classification method [16]. The comparison with the rest of the classifiers usually depicts NN as a dominant classification rate [38] [87]. The popular and advanced NN techniques in pattern recognition include extreme learning machines (ELM), feed-forward back-propagation system (FFBP), recurrent neural networking (RNN) and convolutional neural networking (CNN). The generation of these algorithms has resulted in the resurgence of NN for upper limb practices. Like SVM; these techniques achieve classification rate around 80% or higher [92], [94], [42]. Zhai *et al.*; (2017) proposed higher performance and efficient training by CNN with respect to SVM for different parameters of grasping and force patterns [95]. Kairul *et al.* proposed the application of the Extreme Learning Machine (ELM) to distinguish EMG pattern for different finger movements. The ELM provided classification results better than LDA, k-NN, SVM variants [96]. The disadvantage associated with NN is the chance of overfitting. To avoid overfitting, it requires extensive training of the system which may result in greater time consumption. Under such circumstances; other classifiers like kernel based SVM; fuzzy logic can be employed instead of neural network.

E. Random Forest

Random Forest is a supervised learning method, capable to detect at significantly similar or higher classification rate w.r.t. SVM and NN. The other advantages are fast and efficient processing [91]. Also regarded as "ensemble learning", it is constructed using the majority of trees and class selection is based upon the highest number of trees to be considered [33]. The comparative analysis reported by researchers has shown a better classification rate by random forest as compared to classifiers [98], [99]. Liarokapis *et al.* applied random forest in their studies to design EMG based task-specific control models in reach to grasp studies. The random forest algorithms resulted in higher classification rate and reduced processing time as compared to SVM, MLR and ANN in many cases [100]. Often; the classification accuracies are similar for NN, SVM and RF [91]. Another study by Atzoni *et al.* resulted in a higher but comparable classification rate by convolutional neural network techniques as compared to random forest [101].

IV. Classification of Multi-Modal Systems of Bio-Signals

The human electrical signals normally are unsteady in nature. It is not necessary that signals acquired at a particular instance of the day would repeat at another moment. The factors may include electrode shifting, their inappropriate positioning, fatigue etc. Besides; a human hand is capable to perform enormous finger motion. Certain similar actions may not be clearly recognized with EMGs or EEGs only. To solve such issues, dynamic sensors are incorporated along with biosignal. The mitigation of such sensors with EMGs and EEGs result in more concise activities and improving classification rates. The dynamic sensors, in this context, are the external sensors required to measure limb kinetics and kinematics. Some examples of such sensors are gyroscopes [83], accelerometers [123], load pins etc. The popular utilization of such modality involves in detecting kinetics of human limb along with the muscle behavior. It is essential to mimic simultaneous joint movements. The signal based on the kinematics of limb fused with the EMG signals of the muscles may ease the complexity associated with reach to grasp actions and might allow lesser involvement of muscles. Fougner *et al.* incorporated accelerometers to EMG based upper limb system to evaluate the role of kinematics [124]. Bennett *et al.* designed a combined EMG/IMU[1] based control algorithm to replace a sequential EMG based control system for wrist rotation. The experiment performed on able-bodied and amputees for the designed system showed lesser time required for motion [125]. Further; Alshammary *et al.* also used IMU to detect hand movements for designing a switching scheme for hand and elbow system in the EMG based system [126]. Betti *et al.* used motion capturing for hand movement with EMG and MEPS recordings [127]. Such studies allow performing a more synergistic, faster and controlled motion compared to previous methodologies. Like EMGs; such sensors are employed with EEGs to detect intricate finger movements. Roy *et al.* used flexi force sensors along with EEGs while grasping different objects [89]. More comprehensive research was performed by Yang *et al.* to identify multiple finger motions during dynamic conditions. They employed electrodes to measure EMG and magnetic motion tracking system for hand's position and orientation Unfortunately; based on the kernel-based SVM classification, the accuracy reduced when multimodality was employed as compared to EMG based analysis trackers [117].

Another way can be EMG-EEG combination. It can be used in situations when people suffer muscle atrophy in the limb. Also; such combinations also help to design BCIs capable to perform activities of daily living [128]. However; cost can be an issue in this senario.

[1]IMU stands for Inertial Measurement Unit.

V. Discussion

In this study; the data segmentation, feature selection and feature combinations and classifiers of EMGs and EEGs were discussed. In most of the previous studies; overlapped data segmentation with a window size of 150–200 ms and a shift of around 50–80 ms is preferred. For feature extraction, selection and sets; the time-domain feature combinations are preferred very often as compared to frequency and time-frequency domain feature combinations. The features are diverse which results in numerous permutated feature sets. At times; a single feature might be sufficient for a desired classification accuracy, whereas a feature vector of 10 different features might not classify optimally. Individually; time domain features like WAMP, WL, RMS, MAV, result in better classification accuracy. For a feature set; the two most popular time domain feature sets are Hudgins set of time domain features and TD (time domain feature sets) + nth order autoregressive features [1], [96].

Most frequency domain features are based on the power spectrum of signals and are less preferred. However; recent frequency domain characteristics based on spectral moments may be a step forward in their application in the design of upper limb control systems. The wavelet techniques are also effective to extract information from EMG signals obtained from the muscles. There have been a continuous outpour of new features for better identification of action intention, which require application trails in future [38], [41], [48]. Over two decades; various features and its combination were proposed and their performance was compared by various algorithms.

The popularly used classifiers for different feature sets are LDA, SVM and NN. There are different forms of above mentioned classifiers which are diversified on the basis of their algorithms. For instance; a neural network methodology is based on various parameters. The simplest NN technique; named as MLP will result in lesser classification rate than advanced NN techniques such CNN, RNN. Among different classifiers, random forest is the one which have resulted in highest classification accuracy in optimal time. The features sets used with random forest are RMS, WL SSC; MAVS, WL, MAV, SSC, ZC; Raw Input and RMS + features derived from Spectral moments. It is less frequently used but results in higher classification accuracy [31], [91], [98].

The optimality of bio signals based devices depends on an arrayed amalgamation of different factors such as muscle selection, electrode positioning, filtering techniques, signal conditioning, features extraction, selection and combination and classification or regression. Besides; the transparency of studies and classification rates largely depends on the experimental situations, time and place incorporated in the respective study. Table IV and Table V show selected EMG and EEG based upper

TABLE IV
LISTING OF RESEARCHES DONE ON UPPER LIMB ASSISTIVE DEVICES USING EMG AS ONE OF THE BASIS FOR ACTION

Ref. No.	Segmentation (WS, Inc.: ms)	Muscles/electrode no.	Subject Counts	Features/Feature Sets	Classifier	Optimal Classification	Task
[102]	Overlapped (WS: 250; Inc.: 70)	2 electrodes	5M + 1FM (AB)	MAV, VAR, 4th order AR coefficient (AR4), SE	LDA (Dimension reduction)	95.94% to 98.12%	HG
[88]		2 channel system	6M + 2FM(AB)	SSC+ZC+WL+HTD+SKW+AR5+MAV	Kernel-based SVM and kNN	90%;	HG
[23]	Overlapped (WS:256;Inc.:32)	16 sEMG / intra-muscular system	6 M (AB)	MAV+MAVS+SSC+ ZC+WL+RMS+AR5	MLP and LDA	97%	HG
[40]	Overlapped (WS: 250; Inc.: 125)	6-16	31 AB subjects and 9 transradial amputees:	Hudgin's set of TD features; RMS+AR6; AR4 + 'WL, RMS, SampEn and CC4' HIST9; TD6; TD2; TD4a; TD4b; & TD4c.	SVM	TD4 + SVM: 88.6-77.1%; TD9 + SVM: 89.7 - 78.9	HG
[103]	Overlapped (WS: 256 and Inc.: 32)	64 channels of EMG.	18M AB + 2 stroke patients	Hudgin's set of TD features	LDA	91.66 ± 5.66% (AB); & 82% / 86% for stroke patients	HG
[36]	Overlapped (WS: 128, Inc.:32).	8 electrodes (7 forearm muscles + 1 bicep)	1 subject	RMS/MAV/SSI/TM3/DASDV; IAV/SSI/WL/SSC/ZC; MAV1/WL/AAC/ZC/WAMP; IAV/VAR/TM5/ZC/WAMP.	LDA	ULDA + LDA: 96%-89%	HG
[104]	Overlapped (WS: 200; Inc.:25)	8 bipolar Ag-AgCl electrodes	7M + 3FM (AB)	MAV + WL + WA + VAR	ANN and GP regressor	GP regressor	HG
[105]	Overlapped (WS:256 Inc.: 10)	8 electrodes (right forearm)	11 AB subjects	Hudgins set of TD features, HIST, RMS, Variance	SVM-Poly, SVM-RBF, kNN, MLP, RF	Random Forest: 88% to 91%	HG
[38]	Overlapped (WS: 150; Inc.: 100)	32 sEMG electrodes	8 subjects (with upper limb amputation)	ASS + ASM; ASM + MSR; MAV + WL + WAMP + SSC	ANN	ASS + ASM +ANN: 92% ± 3.11	HG Intention
[106]	Overlapped (WS: 256, Inc.:128)	8 electrodes (7 forearm + 1 bicep)	15 AB subjects	Time Domain Features + AR	Adaptive SVM & Conv SVM	Features + adaptive SVM: 92%±4 %	HG
[29]	Overlapped(WS: 200, Inc.: 50)	2 sEMG and 1 pair of iEMG	8 AB subjects	Hudgins Time Domain Features	N-B Classifier	Hudgins TD feature set: 95±4%	Hand Grasp and HG
[42]	Overlapped (WS: 200, Inc.: 20)	12(AB) & 4 electrodes (amputees).	9M + 7FM (4 partial-hand amputees)	TD + AR features	LDA	96-100 %	HG wrt. wrist positions
[107]	Overlapped (WS: 256 & Inc.:50)	12 sensors: around forearm & extrinsic	22 subjects (20 AB, 2 amputees)	MAV, WL, AR4, LogVar	LDA	60%	Hand motions and HG
[34]	Overlapped (WS: 200; Inc.: 50)	1 intramuscular electrode	7M + 4FM able-bodied subjects	Combinations of WL, MAV, ZC, SSC, WAMP, RMS, EMGenv, MMAV, CSE	ANN; poly 1 model	ANN	Hand Grasping
[87]		12 EMG electrode Positions	8 AB subjects (6 M and 2 FM)	Average EMG, WL and SSC (No feature extraction for ESN)	LDA, SVM, ESN; (NN)	SVM with RBF kernel classifiers	R-G actions
[108]	Overlapped (WS: 150; Inc.: 50)	16 EMG electrodes	14 AB (10M and 4FM)	Normalized EMG	ESN: NN	85.1%- 98.3%	R-G actions
[80, 81]		16 (8 upper arm; 8 forearm muscles)	5 AB subjects	Raw EMG	LDA, SVM, ANN, RF, State Space	Random Forest	R-G
[78]	Overlapped (WS: 1024 & 250; Inc.: 512 & 125)	8 EMG channels	8 healthy subjects (6M and 2FM).	ZC, SSC, MAV and WL	LDA, NB, SVM,	Cubic SVM	FM recognition
[96]	Overlapped	11 electrode pairs on forearm	6M + 3FM (AB subjects)	SSC, ZC, WL, HTD, SS, MAV, MAVS, RMS, AR6; Hudgins; Englehart; Khushaba; Hargrove feature sets	LDA, k-NN, SVM, ELM	SM-SVM and LS-SVM: 92-96 %	FMv
[94]	Overlapped (WS: 150; Inc.: 25)	MYO Armband: 8 channels	7 AB subjects (4 M and 3 FM)	Raw input signals and TD set of features (MAV, WL, SSC, ZC)	CNN, SSAE-r, SSAE-f, LDA	CNN: 97.5%	Hand Motions
[41]	Overlapped segmentation	4 forearm muscles	18 AB subjects (9 M and 9 FM)	iEMG, MAV, SSI, VAR, RMS, WL, DAMV, M2, DVARV, DASDV, WAMP	SVM, ANN, QDA, LDA	QDA: 90.12%; kNN: 89.60% (DAMV)	Hand Motions
[110]	Overlapped (WS: 160; Inc.: 35)	surface and intra-muscular EMG	8 subjects (transradial amputation); & 10 AB	MAV, ZC, SSC, WAMP, WL, MYOP and Cardinality (CARD)	LDA, NN, SVM, NB, k-NN, Decision Tree	NN	Limb Movements
[31]	Adjacent/Disjoint	5 EMG electrodes	8 subjects (5 M and 3 FM)	RMS, features extracted through different ordered moments	SVM; RF	CR: 60-100 %	HG and Digit Force
[95]	Overlapped (WS: 200; Inc.: 100)		51 subjects (40 AB and 11 amputees)	Spectrogram	SVM, CNN	CNN: 79 %	Grasping and Force Pattern
[21]	Overlapped (WS 160, Inc: 40)	12 EMG channels	6M + 4FM (AB subjects) & 6 amputees	IAV, WL, ZC, SSC and kurtosis (KUR); AR + RMS.	LDA	AB subjects: 97% & Amputees: 90%	Grip Force
[77]	Overlapped (WS: 150 & Inc. 50)	6 pairs of EMG electrode	9/8 AB subjects	MAV, WL, ZC, SSC	LDA	90%	

Abbreviations: WS: Window Size, ARn: nth order of AR; CCn: nth order of CC (n = 1, 2,..9); Change; LDA: Linear Discriminant Analysis; SVM: Support Vector Machine; ANN: Artificial Neural Network; CNN: Convolutional Neural Network; RF: Random Forest; k-NN: k-Nearest Neighbor (k = 1, 2, 3…); QDA: Quadratic Discriminant Analysis; SSAE-f: Stacked Sparse Autoencoders with features; SSAE-r: Stacked sparse Autoencoders with raw samples; MLP: Multi-Layer Perceptron; ESN: Echo State Network; SSC: Slope Sign Crossing; M: Male, FM: Females; AB: Able-bodied; HG: Hand Gestures; R-G: Reach to Grasp; FMv: Finger Movement; TD6: (MAV+WL+ZC+SSC + RMS + AR6); TD4a: (WL + LD +SSC + AR9); TD4b: (WL + SSC + AR9 + CC9); and TD4c: (RMS +VAR +LD +HIST9).

TABLE V
LISTING OF RESEARCHES DONE ON UPPER LIMB ASSISTIVE DEVICES USING EEG AS ONE OF THE BASIS FOR ACTION

Ref. No.	Electrode Counts	Subject Counts	Features	Classifier	Optimal Classifiers	Task
[64]	64 electrode system	10 right-handed AB subjects (7 FM and 3 M)	Multi-class CSP; Multi-class stationary Tikhonov regularized CSP; Multi-class CSP based on generalized eigenvector.	SVM	Multi's TRCSP + SVM:	Limbs Action
[111]	64 electrode system	4 right handed AB subjects	CSP algorithm	LDA	CSP + LDA: 74%	Arm Movements
[112]	128 electrode system	7 AB subjects	Regularized wavelet-common spatial pattern algorithm	Fisher LDA	80.24%	Hand movement directions.
[113]	64 electrode system	5 AB right-handed subjects (4M + 1FM)		Linear Model Regression		Fingers movements
[85]			Spatial-Temporal Features	SVM	40%.	R-G
[114]	61 electrode system	15 AB subjects (7 M, 8 FM)	Low- frequency time domain features from 0.3 to 3 Hz	multiclass sLDA	65.90%	R-G actions.
[69]	64 electrode system	10 AB subjects (1FM)	Temporal and Spectral domains	Shrinkage LDA	67.77%	R-G actions & variable force
[79]	29 electrode system	10 AB right handed subjects	Autoregressive Parameter, Hjorth Parameter (HP), Correlation Dimension (CD), Hurst's Exponent	k-NN, SVM	HP + kNN : 97.9%	Decoding Different Grasp types
[89]	29 electrode system	20 AB right-handed subjects	CD in different bands	Multiclass SVM	97.2%	Grasp Patterns
[115]	25 electrode system	14 AB subjects (7FM + 7M)	Temporal features and spectral features and their combinations	LDA	79%	Hand Grasping

limb research studies repectively. The studies are selected on the basis of different experimental techniques like activities selected; electrode type, number of electrodes and muscles selected, subject counts; methodologies of data segmentation method, various features combinations and classifiers and their classification efficiency expressed in terms of classification rate, and processing time. These parameters can be said as important experiment and analysis sets. There is no study to our knowledge which has given an accumulated information for various features and classifiers to design control systems for prosthetic or orthotic devices. Based on this review, a decision tree is drawn to indicate the selection of feature combinations for popularly used classifiers in EMG based upper limb classifiers Fig. 2. The selection is based on their application repeatability in different studies and its classification rate based on experimental sets mentioned earlier. An addition or replacing of a certain feature in a feature set might show some improvement in classification rates. In such cases; processing time is selected as secondary parameter for the selection of optimal combination. Based on individual performance; certain features like AR coefficients, WAMP, WL, MMAV, RMS may significantly influence the classification rate of any particular feature set. This can be done by feature projection and selection techniques.

VI. Future Aspects and Challenges

Despite several years of vigorous research; the use of assistive devices is limited. In future; certain factors are still needed to be addressed for more ease in their applications in daily livings. The main factors are noise-free signal acquisition; compatible sensorized system and robust control algorithms. Based on the papers surveyed; future directions for future research are discussed below.

A. Signal Acquisition; Noise and Artifacts

The parameters such as electrode position; action intention, muscle selection, number of channels were not incorporated in this review. The skin has to be prepared before placing electrodes. It involves cleaning, removing hairs and applying gels [11]. Also; electrode shifting may also result in distorted signals. Identifying the muscles and their counts in a device also may influence action classification/regression results. Higher count of muscles will result in more number of channels which ultimately may result in cumbersome and complex processing and product designing. In general; the studies have shown that the optimal count of channels vary from 5–12 channels. Identification of noisy signals and use of apt filter for it is another stage which must be worked upon in future. Most often; researchers use conventional features for EMG/EEG based devices. The newly proposed features such as ASS, ASM, DFT_MAV2 were not extensively used afterwards. Thus; requiring a need to explore them with different feature combinations. The exploration of correlated features of EMG and EEG feature sets is another aspect which is a subject future research.

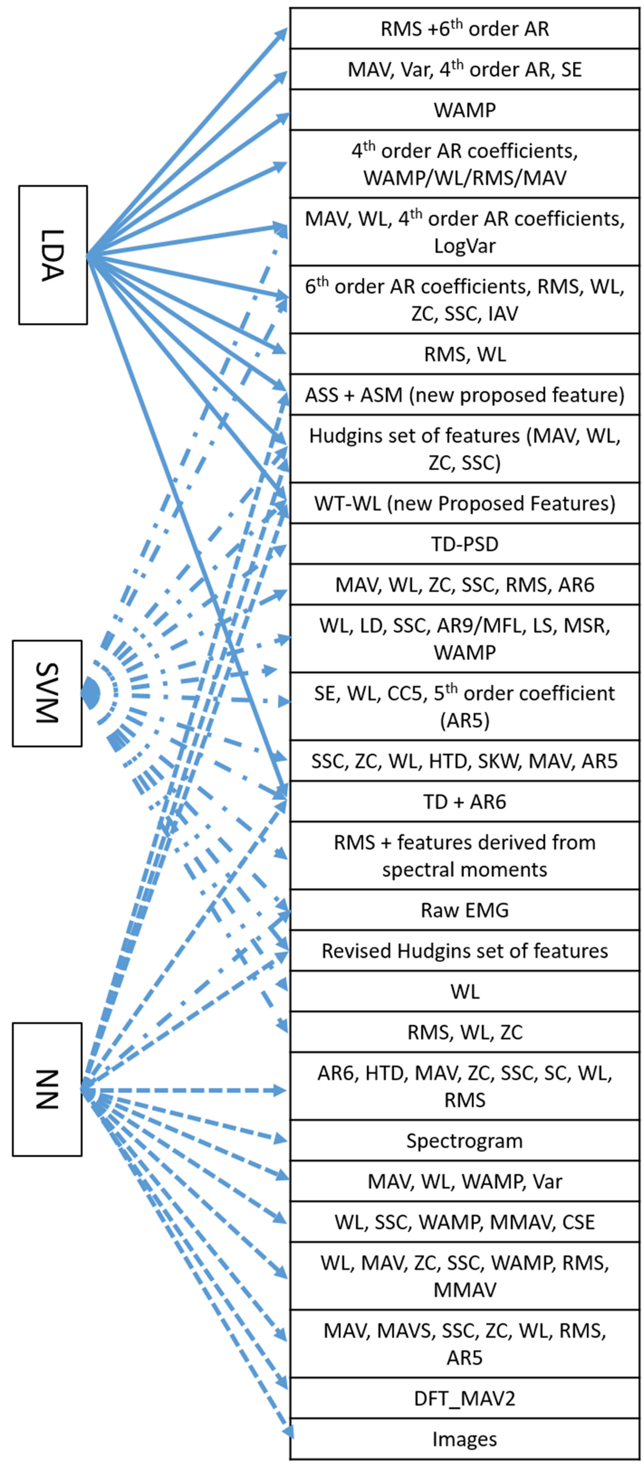

Fig. 2. Various feature sets suggested for three most frequently used algorithms. The decision of selection on these three algorithm was based on the popularity chart shown in Table VI.

B. Multi-Modality

In addition to various gestures and grasping; a human hand has a capacity to detect/perceive various sensation such as pressure, force, temperature, stiffness, vibration etc. These detections are perceived by the thousands of human mechanoreceptors on the palm. However; this cannot be achieved by EMGs or EEGs individually. Various sensors developed over last decade, if used with bio-signals, could help to detect such a sensation. Different force sensing sensors such as potentiometers, hall-effect sensors, and FSR are suggested to detect grip force in various studies. Presently; the modality is largely limited to two sensor system, one of which is the bio-signal based sensory system. To compliant a human hand; various sensation have to be retrieved from

TABLE VI
PREVIOUS WORK WHERE DIFFERENT ALGORITHMS ARE EMPLOYED AS CLASSIFIER FOR EMG/EEG BASED ACTION

S. No	Reference	NN	FL	N-B	SVM	LDA	F-N	GN	kNN	RF
1	[116]		√							
2	[21]				√	√				
3	[96]	√			√	√			√	
4	[108]; [104]; [34]; [80]; [101]; [37]; [118]	√								
5	[82]						√			
6	[20]					√			√	√
7	[117]	√			√			√	√	√
8	[118]				√	√			√	
9	[98]	√			√				√	√
10	[77]; [119]; [36]; [103]; [107]; [102]					√				
12	[87]	√			√	√				
13	[120]; [86]; [123], [76]; [50]				√					
14	[31]	√			√					√
15	[95]	√			√					
16	[27]	√							√	
17	[121]				√	√				
18	[122]				√	√			√	√
19	[78]			√	√	√				
20	[90]				√	√			√	√
21	[29]			√						
22	[99]									√
23	[110]	√			√	√			√	√
24	[42]; [57]; [84]; [47]	√				√				
25	[41]			√		√			√	√

sensors placed in a limited area. This can be achieved by many miniaturized sensors positioned on hand, palm and fingers or by developing a single sensor system which may depict enormous useful information to detect sensation [129].

C. Strong Control System

To capacitate large amount of information from these sensors require a very strong control system. A control system must be capable to detect slightest of the variations taking place. A system of various sensors requires parallel and compliant processing of the data. This requires processing to identify the task or action in a matter of milliseconds. The pattern recognition based classification has been boosted by the acknowledgment of machine learning. Modern day techniques like deep learning and adaptive system based algorithms have the capacity to deal a diverse and abundant set of data. Certain classfication schemes such riemannian geometry classifier, negative selection algorithm are new and have found applications in motion detection using EEG. [21], [88]. Reimannian geometry classifiers are being considered efficient and thus promising in such applications. Lotte *et al.* expressed the need to apply such classifiers in future [14]. However; there isn't any application of reimannan classification schemes for EMGs based control systems to our knowledge. The idea of developing an enhanced adaptive regression system may also improve the repeatability and flexibility of control systems.

D. Improving Real-Time Performance

Very often; the classification results from offline and online control schemes may vary. Generally; it is found that the online classification schemes report lesser accuracy than offline control schemes. One possible reason could be inefficient control schemes and poorer hardware which results in lower classification with time. It is required the identify the causes of such results and improve its results in future.

VII. CONCLUSION

This review elaborates the methodologies associated with two bio signals for upper limb assistive devices. The sensing techniques include electromyography and electroencephalography and their modality. The review helps to identify optimal features and classifiers on the basis of classification rate. The basis of division of EEG based features is similar to EMG based features. The EEG based frequency features are comparably more informative in comparison to EMG based frequency domain features for upper limb applications. Besides; the previous researches were investigated to design a preferred combination of features set and classifiers. The use of classifier can be regarded as a trivial selection method, dependent on the type of feature or feature set selected. Thus, a classifier selection and its parameter optimization is an extremely important aspect. The inter-modality of these sensing methodologies and their modality with other sensing system were discussed. However, such research still lacks concrete selection of multi-modal sensing techniques, which sometimes results in a lower classification rate.

Other human signal sensing mechanisms such MMGs, ENGs have shown motivating results, if not better. However, the subtlety of research on such methodologies has come to no conclusion.

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