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A Review on Electromyography Decoding and Pattern Recognition for Human-Machine Interaction

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ABSTRACT This paper presents a literature review on pattern recognition of electromyography (EMG) signals and its applications. The EMG technology is introduced and the most relevant aspects for the design of an EMG-based system are highlighted, including signal acquisition and filtering. EMG-based systems have been used with relative success to control upper- and lower-limb prostheses, electronic devices and machines, and for monitoring human behavior. Nevertheless, the existing systems are still inadequate and are often abandoned by their users, prompting for further research. Besides controlling prostheses, EMG technology is also beneficial for the development of machine learning-based devices that can capture the intention of able-bodied users by detecting their gestures, opening the way for new human-machine interaction (HMI) modalities. This paper also reviews the current feature extraction techniques, including signal processing and data dimensionality reduction. Novel classification methods and approaches for detecting non-trained gestures are discussed. Finally, current applications are reviewed, through the comparison of different EMG systems and discussion of their advantages and drawbacks.

INDEX TERMS EMG, human-machine interaction, pattern classification, regression.

I. INTRODUCTION

Intuitive interfaces for prosthetic devices, robots and other smart machines, are still inaccessible to the common individual. Although there is a plethora of devices that facilitate HMI, there are obstacles in the use of those interfaces. For example, gesture-based interfaces often rely in vision sensors to capture human behavior. However, vision-based systems are still very challenging to develop and do not provide enough reliability for demanding applications. Besides, vision sensors are typically fixed in space and present limitations, such as occlusions, that reduce their area of action [1], [2]. Wearable sensors are alternative solutions that do not have such limitations, but introduce new challenges and may be cumbersome to wear when not well designed. An example of such a system is shown in [1], where a data glove is used to continuously decode hand gestures. However, hand gestures are insufficient for a reliable and intuitive interaction process. Multimodal HMI interfaces combining gestures, speech, tactile and visual cues are essential for a complete, accurate and reliable interaction process. For instance, an individual can point to indicate a target to a robot, use a dynamic gesture to instruct the robot to move and a static gesture to stop the robot. In this scenario, the user has little or nothing to learn about the interface, focusing on the desired task and not on the interaction modality. Nevertheless, all these modalities require a number of sensors that can be cumbersome to use, namely data gloves, magnetic trackers, inertial sensors, microphones, cameras, etc.

Researchers are looking into the feasibility of using electroencephalography (EEG) and EMG to decode the user's intentions [3]. For example, a data glove that is used to capture hand gestures may be replaced by a forearm band with EMG sensors, making the interaction process more natural since the user does not have to wear a glove. This is one of the current research foci in the EMG field.

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In general, there are two types of EMG sensors, surface EMG (sEMG) and intramuscular EMG sensors (imEMG). imEMG sensors use needles that puncture the skin and contact directly the target muscle. For this reason, imEMG provide better signal to noise ratio (SNR). However, they are intrusive, uncomfortable, painful and difficult to setup. Some researchers have found that there is no significant difference between the two types of sensors when measuring gesture classification accuracy [4]. Despite these results, other authors have found that imEMG are more accurate when the gestures are complex motions, i.e., movements that change multiple degrees of freedom (DOF) of the hand [5]. For these reasons, this review focuses especially on surface EMG sensors.

In this review, the basics of EMG signal acquisition and filtering are presented in Section II. Afterwards, Section III presents a detailed exposition of the state of the art EMG-specific signal pre-processing techniques, feature extraction and pattern classification methods. Section IV is reserved for the review of the current EMG-based applications and finally, in Section V, the current research paths and future challenges are described.

II. ELECTROMYOGRAPHY

This section aims to provide the reader with some introductory knowledge about the nature of electromyography signals. Moreover, we describe the techniques used for EMG signal acquisition, how they can be affected by the environment and their limitations. Understanding the signals is a fundamental step to extract features relevant to pattern recognition and to design an overall robust recognition system. A thorough description of an acquisition circuit, signal conditioning and analysis is presented by Botter *et al.* [6].

A. SIGNAL OVERVIEW

Rather than reading the electric potential on the motor nerves, an EMG electrode reads the electric potential generated in the muscle fibers when they contract. An EMG electrode usually consists of a pair of poles aligned along the muscle fiber direction. There are also sensors with monopoles which measure the potential in respect to other reference electrodes. Monopoles have the advantage of allowing more flexible setups, since any two poles can be connected to obtain a reading. Bipolar electrodes are limited to specific electrode widths. The distance between each electrode pole and their diameter also have a significant influence on the EMG signal [7].

The provenance of signals measured with sEMG electrodes is the potentials generated by muscle cells when excited by motor nerves, rather than the electric potentials within the nerves themselves. However, there is a strong correlation between these two potentials [8]. The EMG potential reading is also correlated with the activation level of muscles and the force they generate. However, this relationship is nonlinear and difficult to model. sEMG signals have inherently low SNR, which means that they are very susceptible to environmental noise. Two important works in the field that study EMG signals and their noise are in [9] and [10]. The first study describes methods to decrease the captured noise, signal artifacts and interferences in EMG recordings, as well as signal processing techniques for noise suppression (e.g. band-pass filtering, adaptive noise cancellation filters and filters based on the wavelet transform). In [10], Piervirgili *et al.* found that the environmental noise can be significantly reduced by rubbing the skin surface with an abrasive conductive paste. Other authors propose empirical mode decomposition (EMD) in order to suppress signal noise [11], [12].

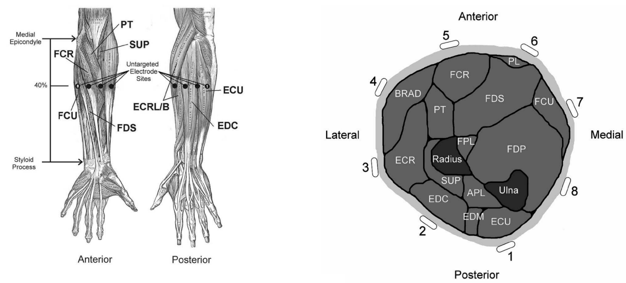

FIGURE 1. Longitudinal and transverse representations of the forearm muscles, adopted from [4].

sEMG electric potentials are acquired with electrodes placed on the surface of the skin just above the target muscle, which is a non-invasive technique. A graphical representation of the forearm muscles is presented in Fig. 1, [4]. The signals obtained from these muscles are particularly interesting for the actuation of hand prostheses and gesture recognition. Farrell and Weir [4] found that with adequate processing techniques, pattern recognition on signals measured with non-targeted electrodes can be as successful as when measured with targeted electrodes. While a targeted electrode is defined as a surface electrode that is carefully positioned above the target muscle, a non-targeted electrode is placed above the muscle of interest but without concern for its positioning accuracy. An example of non-targeted electrodes are the elements of a linearly spaced array of electrodes. Such a setup is likely to capture signals from several muscles simultaneously. On the other hand, Farrell did not study the effects on pattern recognition (PR) accuracy caused by issues such as electrode lift-off and shift.

The surface of the electrodes is typically silver and the contact with the skin can be either wet, using a silver-chloride gel, or dry (without any medium) [13]. Wet contact electrodes offer lower skin contact impedance, which reduces the effect of external interference sources on sEMG electrodes and improves SNR. However, the use of a gel is an inconvenience for a user who might place and remove the electrodes several times a day. On the other hand, since dry electrodes do not require the use of a gel, the setup procedure is simpler. Furthermore, they are typically kept in place by an elastic band rather than an adhesive, meaning that they are fully reusable. This would enable a user to wear and remove the sensors whenever necessary, which is especially important for a user-friendly HMI system.

When the focus is the discrete pattern recognition of sEMG signals, it is important that each pattern/class remains consistent between experiments and that the features discriminate the classes correctly. The consistency is very dependent on the chosen set of features and can be negatively influenced by electrode shifts, changes in arm posture [14], fatigue and electrode-skin contact impedance, which changes in the presence of sweat [8]. EMG signals of the forearm muscles can be successfully decoded independently of the subject's gender and dominant hand [15]. Nevertheless, the study presented in [15] was limited to the control of upper limb prostheses and used only 5 classes, obtaining around 90% of recognition rate (RR).

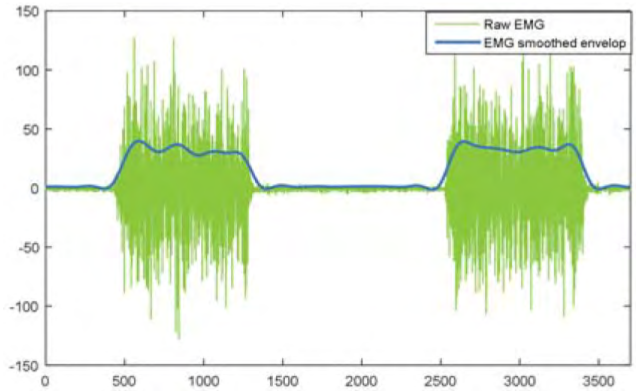

FIGURE 2. sEMG signal enveloping, adopted from [16].

B. SIGNAL FILTERING

Although there are many different approaches to sEMG signal pre-processing, most sensors use high-pass filters in the range of 10 to 50 Hz (sometimes higher) and low-pass filters of around 500 Hz. Most of the times, a notch filter is also used to remove power line interference at 50/60 Hz. Signal amplification is also necessary to improve the quality of its digitization. The amplification is usually between 500 and 2000 fold. Bipolar electrodes are typically arranged with a differential amplifier in which the potential difference between the two poles is amplified. This type of amplification is less likely to capture external noise or signals from distant muscles.

In [17], Guerrero *et al.* present a novel circuit for a double differential active electrode with comparatively low complexity and cost. It is composed by a single quadruple operational amplifier and few passive components, allowing accurate recordings of sEMG signals with dry contacts while also maintaining the advantages of differential amplification. This circuit configuration is also shown to reduce crosstalk between electrodes.

One of the first studies on EMG-based pattern recognition uses a band-pass filter (BPF) of 10 to 500 Hz in which the signal is amplified 1000 times and digitally sampled at a rate of 1 kHz [18]. Wet disposable electrodes were used on the *biceps brachii* and on the lateral head of triceps. The system was tested with six types of motion: elbow flexion and extension, wrist pronation and supination, and humeral (shoulder) rotation in/out. Other authors propose the use of a notch filter to reduce power line-induced interference [19]. A 30-400 Hz BPF was used and the signal is sampled by an AD converter at a rate of 2.5 kHz. The authors claim that the proposed filtering scheme avoids unstable signals for EMG pattern classification. Another study proposed a similar setup where the sEMG signals are filtered with a 20-500 Hz BPF and digitally sampled at 2 kHz [20]. In this case, the authors built a large acquisition prototype device with 57 wet contact sEMG electrodes (5 mm diameter). A reference study in the field uses a 20-450 Hz BPF on their sEMG signals with sampling rates of 1 and 2 kHz [2]. The authors built a self-contained signal acquisition armband (BioSleeve) with 16 dry-contact sEMG electrodes. Fig. 2 shows a smoothed signal from sEMG data after being pre-processed using a BPF and a low-pass filter [16]. A 10-500 Hz BPF (digital 4-order Butterworth filter), a notch filter at 50 Hz and a sampling rate of 1024 Hz was proposed in [21]. The authors reported the successful control of an upper limb power-assisting exoskeleton with four electrodes on the upper limb: biceps-short head, triceps-long head, *flexor carpi radialis* and *extensor carpi radialis*. An EMG acquisition system dedicated to medical studies with a BPF of 90-450 Hz band and 1 kHz sampling is described in [15]. This system has a common-mode rejection ratio (CMRR) above 100 dB. It uses 6 channels arranged equidistantly around the forearm.

One of the advantages of systems that use dry contact electrodes, such as the BioSleeve system [2], is that they do not require precise placement of their electrodes. We consider this feature an advantage because the electrodes are placed on the forearm without gluing them to the skin, decreasing the discomfort the user feels. However, dry contact electrodes may experience slippage during a recording session, which must be prevented with mechanical forces (e.g., springs) or corrected in post-processing. Furthermore, the position repeatability of the electrodes is typically low, especially if the user is not a specialist, so post-processing is a better solution for the average user. A software-based solution benefits from high density electrode arrays since it greatly increases the likelihood that the relevant data points for gesture recognition are picked up by the electrodes.

In [22], Spanias *et al.* propose a method for the detection and compensation of disturbances in EMG recordings caused by issues such as electrode shift, liftoff and short-circuit. The detection is achieved by setting a threshold to a log-likelihood metric. When a disturbance is detected, the EMG data are disregarded and the classification only uses the undisturbed mechanical sensors, effectively minimizing the error caused by the EMG disturbances on the prothesis' control loop. In another study, the use of high-density (HD) EMG to overcome problems such as electrode shift and channel malfunction is proposed [23]. When a longitudinal shift (in the direction of the muscle fibers) is simulated, the recognition

TABLE 1. Summary of EMG signal filtering and power line suppression methods.

Authors	Classes/ Channels	BPF Range (Hz)	Sampling Frequency (kHz)	Power Line Suppression Method	Comments
Mewett *et al.*, 2001 [24]	1/1	10-500	2 kHz	• Second order recursive digital notch filter • Regression-subtraction • Spectrum interpolation	• Notch filter works well for simulated interference, but not for real interference; • Regression-subtraction and spectrum interpolation performances are superior, but depend on each specific use case.
Mewett *et al.*, 2004 [25]	1/1	10-500	2 kHz	• Second order recursive digital notch filter • Spectrum interpolation	• Spectrum interpolation performed similarly to, or significantly better than, the notch filter.
Levkov *et al.*, 2005 [26]	1/1	(a)	500 Hz	• Subtraction procedure	• Successfully reduces power line noise from ECG signals.
Malboubi *et al.*, 2010 [27]	1/1	(a)	10 kHz	• Adaptive Laguerre filter with fuzzy step size	• This filter successfully eliminates power line interference from EMG signals and it was more effective than other adaptive algorithms.
Phinyomark *et al.*, 2014 [28]	4/1	20-500	1024 Hz	• 50 Hz notch filter	-
Botter and Vieira, 2005 [29]	16/96	10-500	2048 Hz	• Filtered virtual reference (FVR)	• FVR method attenuates the power line interference on monopolar EMGs.
Niegowski *et al.*, 2015 [30]	64/1	1-500	2048 Hz	• Non-negative matrix factorization (NMF)	• NMF method also reduces the baseline wander from single-channel sEMG signals besides power line interference; • The method outperformed two reference methods (Butterworth filter and polynomial quasi-harmonic modeling).
Afsharipour *et al.*, 2016 [31]	128/1	10-750	2048 Hz	• Spectrum interpolation	• Signal quality and information content are not affected for 30 min.

(a) Not available.

accuracy decreased from 96% to about 90%. A transverse shift (perpendicular to the direction of the muscle fibers) caused a reduction to about 80%. This technique is also accurate even when a large proportion of channels is omitted.

A common challenge related to electrode-based sensor systems such as EMG or electrocardiography (ECG) is how to avoid or reduce external noise captured by the sensors. These systems must be able to deal with different interference sources such as the electric power source which feeds the acquisition hardware. Owing to the low amplitude characteristic of EMG signals, they are easily overwhelmed by electrical disturbances. In order to reduce their negative effects in the output signal, some guidelines should be followed during the design of data acquisition setups, namely:

1) Arranging cables so that inductive and capacitive coupling between different channels is minimized, e.g., separating wires connecting distinct electrodes [7];
2) Using differential amplifiers and/or a reference electrode for common-mode rejection [15];
3) Skin preparation (shaving and/or rubbing with an abrasive conductive paste) in order to reduce the difference between the electrode poles impedances [10].

In order to remove power line noise from raw recorded EMG signals, the use of different post-processing methods have been proposed. Examples are second-order recursive digital notch filters at the power line frequency, regression-subtraction [24] and spectrum interpolation [25]. In the cases where a battery is used as a power source, its wires may also introduce noise into the output signal because of electrode pole impedance unbalances. These impedances change over time in sEMG electrodes due to disturbances in the electrode-skin interface. Table 1 summarizes a list of studies with an emphasis on signal filtering and suppression of power line noise.

C. ELECTRODE ARRAYS

Researchers have been using high-density (HD) arrays of electrodes for the acquisition of EMG signals in both the longitudinal and transverse directions of muscle fibers, which may eliminate the need for precise placement of the electrodes, as mentioned in the previous section. The increase in the number of channels also increases the likelihood of capturing key EMG patterns. When electrode shift or liftoff occurs, the topographical map of relative muscle activity should stay roughly the same but shifted in a certain direction. However, increasing the number of channels, also adding redundancy, requires proportionally more computational power to post-process the signals and to extract regression/classification features. The detection and correction of electrode shift also add complexity to the recognition system.

Liu and Zhou use 57 EMG channels of which 48 are arranged in a 6x8 grid (6 straps with 8 electrodes each) and the remaining 9 channels are distributed across 3 other locations [20]. These locations are the first dorsal interosseous (FDI), the thenar group and the hypothenar group. A lower density array with 16 electrodes (4 straps with 4 bipolar electrodes each) is presented and evaluated in [2]. The measurements used dry contact electrodes worn in the forearm which were kept in place by a stretching sleeve. This system showed a high accuracy on gesture classification without precise positioning of the electrodes. However, the gesture classes must be retrained on each recording session.

Tkach *et al.* [32] tested various electrode grid sizes, between 3x2 and 4x4, on transhumeral and shoulder disarticulated amputees who went under a targeted muscle reinnervation (TMR) surgery. A major difference from other approaches using electrode grids is that their arrangement includes electrode poles connected across different muscle groups. The authors indicate that it is possible that electrode pairs in the transverse direction may record regularities in activation patterns across different muscle groups, improving PR accuracy. On an earlier study, the authors demonstrated that wider inter-electrode spacing is beneficial for PR.

Celadon *et al.* [33] have been studying the use of monopolar high-density arrays (192 channels). This number of channels leads to a very high dimensionality of the EMG feature set, which in turn increases the post-processing computational load. Online reduction of the number of channels is proposed by the analysis of the topological distribution of the activity areas and limiting feature calculation to areas with significant activity. Nevertheless, the authors found that the classification accuracy always decreases when EMG channels are dropped, using a linear discriminant analysis (LDA) classifier.

High-density electrode grids have also been used for EMG signal decomposition [34], [35]. EMG signals are composed of superimposed motor unit action potentials (MUAP) trains which cause motor units (MU) to contract. Therefore, it should be possible to correlate complex EMG signals with the firing of individual MUs. Solving this problem would allow the detailed identification of the muscle contractions and the force they generate, effectively opening the way to improved prosthetics control, HMI and medical diagnosis. In [34], Ning *et al.* propose the use of the K-means clustering (KMC) method combined with modified convolution kernel compensation (CKC) in order to reconstruct innervation pulse trains (IPT) from EMG signals. A novel CKC technique was proposed for real-time implementation, requiring processing of about 3 s of EMG signal in the initialization stage [36]. Rasheed *et al.* [37] a Matlab toolbox with their approach to EMG signal decomposition into MUAP trains. In [3], Biagetti *et al.* present a technique for parametric model estimation of MUAP from EMG signals using homomorphic deconvolution. Fast independent component analysis (FastICA) can also be used for the identification of MUs from HD-EMG grids [38].

III. PATTERN RECOGNITION

This section presents the state of the art methods used in the recognition of recurring patterns in EMG data streams. Pattern recognition usually has three stages:

1) Signal pre-processing: reduction of the influence of external noise sources and SNR improvement;
2) Feature extraction: determination of the gesture pattern predictors;
3) Classification.

This section is structured according to the aforementioned stages. Feature extraction may originate feature vectors of relatively high dimensionality, whether because a large number of distinct features was chosen or because the number of signal channels is large. High dimensionality of the input space of classification predictors may decrease the performance of classification models in many cases. Therefore, some authors propose data dimensionality reduction techniques to face this challenge. The issue of novelty detection (detection of untrained actions/gestures) has also been studied during the past few years. This is an important topic in the area of pattern recognition that is seldom studied. Often-times, the classifiers perform well on the classification of trained patterns, yielding good results on benchmarks. Despite this, non-trained patterns may still be wrongly classified as one of the trained classes.

Most research studies in EMG-based PR follow a discrete recognition approach. This means that classification models are trained, tested and run with finite segments of data that represent examples of each one of the pattern classes. On the other hand, there are researchers that are modeling the tension or extension of a muscle using continuous EMG data, i.e., regression of a physical quantity. In this case, the objective is not to label recurring patterns in the data, but to use the measured force or extension of a muscle to control the actuated joint's angle or torque. The methods currently used for regression of physical quantities from EMG data are presented in the sub-section III-E.

A. SIGNAL PROCESSING AND FEATURE SELECTION

The selection and extraction of features from real signals is one of the most important steps in the development of a PR system. This step may reduce undesirable parts of the signal data and emphasize more relevant data. A thorough study of several time domain and frequency domain features is presented in [39]. Strategies for feature selection and redundancy avoidance are also presented. From the 37 time domain and frequency domain features studied, the EMG features which provided the best performance were: mean absolute value (MAV), waveform length (WL), Willison amplitude (WA), auto-regressive coefficients (AR) and two different modifications to the mean absolute value (MAV1 and MAV2). This study states that EMG features based on frequency domain are not well suited for EMG signal classification.

Park and Lee [18] implemented a PR system combining several types of EMG features simultaneously. Although the inclusion of additional features with poor separability may degrade the performance of a PR algorithm, the authors tested the integral absolute value, difference absolute mean value, variance, auto-regressive (AR) model coefficients and linear cepstrum coefficients. The Dempster-Shafer theory of evidence was used as an evidence accumulation method applied through a fuzzy mapping function. A 4th order AR model was applied to extract features from an EMG signal [19]. This approach rejects all input EMG pattern classes not included in the training data of the classifier, improving classification performance. Earlier, Hu and Nenov [40] tested a similar model which performs relatively well. Their implementation relies on the extraction of features for each signal acquisition channel on 400 ms windows at 2.5 kHz. Besides the AR coefficients, which provide 4 features, they also build an EMG histogram (HEMG) with 9 bins, totaling 13 features per channel.

A novel technique that aims to remove user variability from sEMG samples is presented in [41]. In this scenario, the same system can correctly classify samples from new users without retraining. This is achieved with a bilinear model to extract user-independent features. The model can be rebuilt for a new user after only one single motion example is performed, which can be seen as a calibration step. The user-independent signal features are split into windows of 128 timesteps and incremented by 25 steps. The classifier used is a support vector machine (SVM), which takes as input features the channel-wise root mean square (RMS) value of the window's data. Their tests were performed with a 4 EMG channel setup for 5 distinct hand gesture classes. To evaluate the performance of the bilinear model, the authors use the leave-one-subject-out approach, in which one subject's data are used as test data, and the remaining users' data are used to train the model. The classification accuracy on the test (new) subjects is 73±13%, while the baseline performance, without the bilinear model, for new users, is 54±11%.

In [20], three sets of features, (1) a set of time domain (TD) features, (2) 6th order AR (6-AR) coefficients + RMS, and (3) TD + 6-AR + RMS, resulted in 4, 7 and 11 features per channel, respectively (228, 399 and 627 features, in total). This dimensional space is relatively high for pattern recognition, so two dimensionality reduction methods were compared, principal component analysis (PCA) and uncorrelated linear discriminant analysis (ULDA). The best results were achieved using ULDA reducing the number of features to 6, which is the maximum number of linearly independent feature dimensions for a 7-class problem. These results were achieved using of windows of 256 ms with a step of 32 ms. Wolf *et al.* [2] analyze the signal on 500 ms windows, at a rate of 10 Hz, resulting in an overlap of 400 ms of data between consecutive windows. The features are the standard deviation (SD) of the signal during each window. The authors claim that there may occur significant amplitude offsets over time on the signal's RMS, making this feature unsuitable for PR. On the other hand, the SDT is correlated to the signal's strength and invariant in respect to amplitude offsets. An Inertial Measurement Unit (IMU) is used to detect motion of the arm in respect to the body and the surroundings. The window length used for EMG signal analysis can vary significantly. For example, in a recent study, the authors analyzed sEMG signals in windows of 300 ms and 125 ms [42]. While on the 300 ms experiments the authors used disjointed windows (no overlap), the experiments with 125 ms windows had 90 ms overlaps. The proposed classification model was based on boosted classification with majority voting. The classifiers that were trained with windows of 125 ms showed significantly lower error rates. Another study combines a CyberGlove and a tactile force measurement system (FingerTPS) with 16 EMG channels, where the signal is analyzed in windows of 300 ms with 50 ms steps [43]. This study had 10 classes of motions and the attained accuracy was 92.75% using just the EMG signal RMS.

Tkach *et al.* [32] propose electrode grids of 14 or 15 EMG channels, depending on the subject's type of amputation. Electrode pairs are connected in the transverse and diagonal directions. The signal was amplified 4800 times, sampled digitally (16 bits) using a custom-built data acquisition (DAQ) system at 1 kHz, high-pass filtered at 20 Hz and low-pass filtered at 450 Hz using 2nd order Butterworth filters. The signals are processed in 250 ms windows and with a step of 50 ms. In a recent study, Ortiz-catalan *et al.* [44] extract features from 200 ms windows, with 50 ms increments. Two types of electrode arrangements were considered, one with 4 electrodes (for 11 motion classes) and another with 8 electrodes (27 classes). The features selected for both configurations were: MAV, number of zero crossings (ZC), slope sign changes (SSC) and WL. Raw sEMG signals measured with a frequency of 1 kHz were passed through a BPF with bandwidth of 10-450 Hz to calculate wavelength features and control a prosthetic hand for forearm amputees [45].

In [15], Riillo *et al.* propose the use of a supervised algorithm based in Common Spatial Patterns (CSP) to improve class separability. This technique is applied before feature

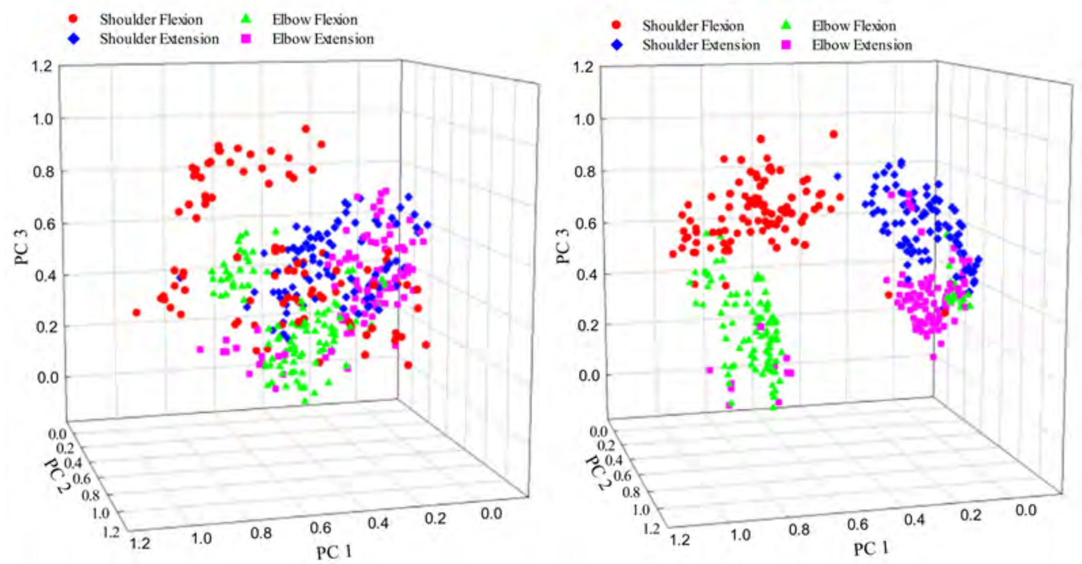

FIGURE 3. The first three principal components of feature maps: for TD features on the left, and features processed with the STFT-ranking technique, on the right, adopted from [46]. The features show smaller intra-class dispersion and better separability.

extraction and improves the SNR of the sEMG recordings. Spatial filters are implemented to maximize the variance of one class while minimizing the variance of the remaining classes by projecting data into a subspace.

A novel short-term Fourier transform ranking feature (STFT-ranking) was recently introduced in [46]. Comparing to the usual arrangement of TD and fractal domain (FD) features, STFT-ranking reflects better the relationship between EMG signals of different muscles. It also normalizes the features to a fixed discrete range, with unit increments between 1 and the number of channels. The Fourier transform is used to retrieve the frequency coefficients from windows of data. The number of coefficients is typically high, so they are combined into a lower number of bins and then ranked, being attributed the score 1 to the highest combined coefficient. Thus, the number of features obtained is the number of bins per signal channel. Even then, the dimensionality may be too large for a machine learning problem, in which case further dimensionality reduction may be necessary, by means of PCA or other techniques. Since STFT-ranking ranks the contribution of individual EMG channels, it must be used with more than one channel. An example of the improvement of class separability with the STFT-ranking technique is shown in Fig. 3.

Coelho and Lima [47] evaluated the use of fractal dimension methods to extract EMG features. Their experiments involved the classification of 7 distinct limb motions using 8 EMG channels. The study of the impact of multiple dynamic factors (forearm rotation angles and contraction force levels) on pattern recognition is detailed in [48]. The authors showed that time-domain power spectral descriptors (TD-PSD) and discrete Fourier transform (DFT) features allowed superior accuracy. Liu *et al.* [49] proposed an invariant feature extraction (IFE) framework based on Fisher kernel discriminant analysis (FDA). This method minimizes intra-class deviation of features extracted in different days and maximizes the inter-class dispersion (class separability). These improvements may allow the training of classifiers with better generalization capabilities.

There is no clear solution to sEMG channel and feature selection for PR-based prostheses controllers. Deterministic methods have been applied to select the feature-channel pairs that present the best results in the classification of hand postures at different arm positions [50]. Two methods are proposed, namely distance-based feature selection (DFSS) to determine a separability index and a correlation-based feature selection (CFSS) method to measure the amount of mutual information between features and classes. The two methods demonstrated better classification accuracy than experiments that used all of the available features. When compared to DFSS, the CFSS method requires less feature-channel pairs for the same performance.

The influence of sEMG data provided by anterior and posterior muscles of a forearm in the control of finger flexion movements is demonstrated in the context of prosthesis development and control [51]. This study claims that the posterior muscles are the main contributor for simple finger flexion whereas the anterior muscles are the most important for complex finger flexion. Simple flexions include the movement of a single finger at a time, while complex finger motions occur when two or more fingers move concurrently. Nevertheless, it is suggested that some simple and complex finger flexion motions can be identified from either posterior muscles or anterior muscles, so there is data source redundancy in the classification of both types of motion.

EMG signals may vary significantly depending on the user, namely due to differences in body composition, muscle size and electrode positioning. To solve this problem and obtain a robust and simple multi-user interface, an automated user calibration method is highly desirable. Cannan and Hu try to partially solve this problem by establishing a linear relationship between the Maximum Voluntary Contraction (MVC) and the upper forearm circumference [52]. MVC is defined as the maximum ability to contract muscles, i.e., the maximum attainable EMG signal. The MVC allows the definition of an activation threshold that has better performance than the RMS or MAV. This threshold is then used to normalize EMG signals across different subjects and improve motion classification accuracy. Their experiments used 4 Biometrics differential EMG electrodes and DAQ system, a Dynamometer hand grip strength sensor, and a custom-built extensometer to measure the forearm's perimeter. The hand grip strength measures the force the subjects exert when closing the hand, which is proportional to the force being exerted by the forearm's muscles. The extensometer is composed of a load cell whose ends are connected by an elastic band worn tightly around the forearm. Hooke's law allows the determination of the perimeter of the cross-section of the forearm as a function of the force measured by the load cell. The authors showed that EMG signal thresholds determined using the proposed method (as a function of forearm circumference) perform better than fixed thresholds calculated from a small group of subjects. In other words, the circumference is a better predictor of the maximum EMG signal that new subjects can generate than the average maximum signal estimated from a subset of subjects. The study also showed that the body mass index (BMI) of an individual changes the MVC value, since the BMI is related to the thickness of the subcutaneous tissue, which in turn has an effect on the muscle-electrode interface impedance..

B. DIMENSIONALITY REDUCTION

An efficient data dimensionality reduction technique reduces intra-class variability while increasing inter-class distance, thus simplifying the classification task. Class separability measures the distance between data points of different classes [47]. Good class separability indicates that data points of a class have a distance from points of other classes greater than the distance between points of the original class. Thornton's separability index (SI) has been proposed for the design of machine learning systems [53].

PCA is a commonly used linear dimensionality reduction technique. It is an unsupervised method which is invariant in respect to the data points' classes [15]. PCA performs an orthogonal linear transformation that projects the data onto a new lower-dimensional space with decreased dimension correlation. The resulting eigenvectors (or principal vectors) are the basis of the new space. The eigenvalues determine the variance of the data in the direction of the respective eigenvectors. Low eigenvalues mean that the data have reduced variance on that dimension, so the dimensions with the lowest eigenvalues can be truncated without losing a significant amount of information. The importance of having relevant embedded muscle activity features in a low-dimensional space is highlighted in [54]. This study shows how PCA can be used as an unsupervised feature extraction method and illustrates the efficacy of this method in capturing features from sEMG signals.

Naik and Nguyen [55] studied the performance of the Non-negative Matrix Factorization (NMF), another dimensionality reduction method. NMF reduces dimensionality by approximately factorizing the source data into two matrices [56]. The factorization is based on the minimization of a cost function that is inversely proportional to the quality of the approximation. If there is latent structure in the source data, the approximation will be effective in lower dimensional spaces. Some studies have found that NMF can be used for the determination of muscle synergies on EMG signals [8]. NMF establishes a constraint of non-negative data only, which is not valid for raw EMG signals. Nevertheless, the inversion of the negative values of EMG signals is sufficient to obtain good results in EMG signal decomposition. Another approach is the application of NMF to the signal's RMS. Other methods for dimensionality reduction are ULDA [20], the locality preserving projections (LPP) and neighborhood preserving embedding (NPE). A method based on discriminant analysis (OFNDA) is proposed in [57].

From a clinical point of view, sEMG is considered to be a good data source for the control of multifunctional upper limb prostheses, due to its noninvasive nature and comfort of use. However, sEMG generates redundant data which may be detrimental to the performance of prostheses control systems. In order to extract significant information from sEMG raw data and successfully recognize the motions an amputee intends to do, a promising approach based on independent component analysis (ICA) is proposed in [58]. Achieving a classification accuracy above 95% for a library of 11 gestures, this approach encourages further developments in real-time prosthetic applications.

Finally, it is important to reinforce that a wrong application of a data dimensionality reduction method may lead to the loss of information that may introduce new failure modes on the classification task.

C. CLASSIFICATION

Human action recognition is achievable by applying PR on EMG signals. Static and dynamic hand and arm gesture recognition is an active research topic, existing several different methods for its implementation. Some researchers use PR to recognize motion intention, such as the contraction of a muscle [21], [32]. Another important classification problem is novelty detection. In this case, the recognition system must also recognize when a pattern does not fit any of the trained classes, as proposed in [19]. Novelty detection is implemented prior to the pattern classification with a one-class classifier called support vector data description (SVDD). The authors also mention that there are several other promising methods for this type of classification: one-class SVM, the single-class minimax probability machine (MPM) and the kernel PCA (KPCA) method. Despite being supervised classifiers, they only have to be trained with the target patterns. This is true for most of the one-class classifiers.

In [59], Alkan and Günay compare the classification accuracy of discriminant analysis methods against a SVM. The only feature retrieved from the EMG data was the MAV and the number of classes considered was 4 (upper-arm movements). The achieved accuracy was better for the SVM classifier (99%) using 10-fold cross validation, while discriminant analysis models achieved accuracies in the range between 96% and 98%.

A self-recovering PR system that relies on LDA for classification and allows online retraining using an optimized LDA-based retraining algorithm is presented in [60]. This system is designed to detect and overcome disturbances on the EMG signal. It is able to retrain the classifier for 3 classes and 4 channels in 0.55 ms, which does not affect real-time usage. The system reaches a recovery rate of 93.5%, which means that it substantially reduced the number of errors after retraining. It is unknown if the algorithm is as efficient for a larger number of classes, or if the retraining time increases exponentially with the number of classes.

A classification system of finger movements for dexterous hand prosthesis control using sEMG is presented in [61]. The system was tested on both intact-limbed subjects and transradial amputees. The effect of the number of electrode channels (NCh) on the classification accuracy was also studied. It was concluded that the accuracy increases with a higherNCh. Nevertheless, 6 channels allowed an accuracy of 98% over 10 intact-limbed subjects on 15 classes (class-channel ratio of 2.5). They used 6th order AR coefficients and TD features (RMS, waveform length, number of zero crossings, integral absolute value and slope sign changes), a total of 11 features per channel. Both PCA and orthogonal fuzzy neighborhood discriminant analysis (OFNDA) were tested for dimensionality reduction. OFNDA presented the best results, while also being suitable for applications with a large number of pattern classes. The reported classification accuracy was achieved using LDA. A recent study proposes the classification of EMG signals using multi-scale principal component analysis (MSPCA) for denoising, discrete wavelet transform (DWT) for feature extraction and decision tree algorithms for classification [62]. It is reported that the best performance (96.67% classification accuracy) was achieved with a combination ofDWT and a random forest classifier.

A PR system was applied to discriminate 6 hand grasp patterns and one rest pattern (7 classes) in patients with spinal injuries (degraded motor control of the upper limbs) [20]. The authors propose a data segmentation scheme based on the amplitude of the EMG signals to determine the onset and end of active segments. Two different classifiers were studied, LDA and k-nearest neighbors (KNN). The majority vote was used as a post-processing method to make the final classification decision. There are a total of 17 deciders (centred window – 8 time steps before, 8 after, 1 in between), each using data with time offsets of 32 ms, which in turn means that there is a decision delay of 272 ms in respect to the newest time step. The achieved accuracy was 97.20±4.0% for a single model, and the majority vote increased it to 97.93±3.3%. The results are influenced the most by the feature set and less significantly by the classification model itself.

A new classifier for sEMG signals, boosted random forests (MCLPBoost), allows the detection of novel patterns [42]. In this work, the data were obtained from 6 subjects, from 6 EMG channels, which repeated each class 42 times. The chosen features were all TD features: MAV, ZC, SSC, WL. The proposed classifier achieved a RR of 92% but the novelty detection accuracy was just 20%. However, the authors propose the use of a threshold on the sample score provided by the classifier, where samples that do not reach the threshold are considered to be novel. A low threshold prevents the detection of novel classes and higher thresholds cause more trained patterns to be classified as novelty. The authors tuned the threshold so that there is a novel detection accuracy of 80%, but concurrently the RR in samples of trained classes decreased to 80%. Wavelengths from sEMG signals of forearm amputees were used as input to a regression artificial neural network (ANN) that estimated the hand shape (joint angles of each finger, wrist pronation/supination angle and palmar flexion/dorsiflexion) in order to control a virtual prosthesis hand, Fig. 4, [45]. Experimental results for a motion set with 4 pattern classes showed an average normalized joint angle RMS error of 0.164.

An interesting approach relies on the overlapped windowing technique, with a length of 300 ms, and 75 ms of delay between windows [15]. EMG features were extracted for each channel and window. Four time-domain features were tested: mean (M), RMS, WA and SSC. PCA was used to reduce the dimensionality of the feature vector and the classifier employed was an ANN with 10 hidden nodes (5 classes). The highest accuracy was achieved using a feature combination of M, RMS and WA, achieving an accuracy of 88.85% ± 7.19% on 20 different subjects.

In a recent study, EMG signals were used to classify 10 classes of motion intention using three different approaches: Fuzzy Gaussian Mixture Models (FGMM), Gaussian Mixture Models (GMM) and SVM [43]. The study describes thoroughly the algorithm used during the training process. The acquisition setup is composed by 16 EMG electrodes carefully placed over a predefined set of muscles, while a single feature is extracted from each channel (RMS). This setup achieved a maximum overall RR of 92.75% with a distance-based FGMM. The GMM and the SVM reached average recognition rates of 87.25% and 88.13%, respectively.

In a different approach, TD and AR features calculated on windows of 250 ms were extracted from 14 to 15 EMG channels [32]. The TD features were MAV, ZC, SSC, WL and 6th order AR coefficients, a total of 10 features

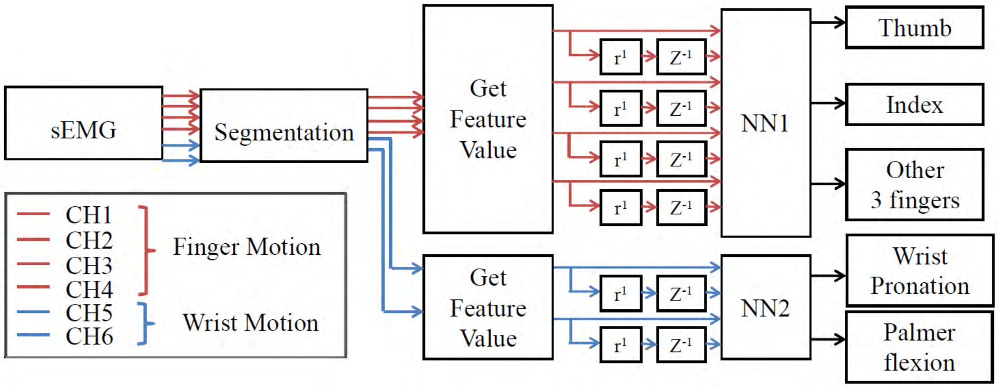

FIGURE 4. Framework for an estimator of the finger and wrist joint angles, adopted from [45].

per channel. The chosen classifier was LDA and no dimensionality reduction technique is mentioned. The number of motion classes can be as high as 29, including 8 single joint movements (elbow flexion/extension, wrist flexion/extension, wrist pronation/supination, hand open/close), 20 combinations of two of these movements and a class without any motion. Their classification error was relatively low when using only 9 classes (1.3%). However, increasing the number of classes to 13 caused the error percentage to increase to 17.1%. The authors also implemented real-time sets of tests called Target Achievement Control (TAC). These tests consisted on moving a virtual limb from a nominal position to a target posture and maintaining it for 1 second. To evaluate the controllability in the TAC test, 3 metrics were used for each classifier: completion rate (percentage of total trials completed within 5 s), completion time and length of movement error (length of movement beyond the minimum required distance). The average length error was 27%, the average completion rate was 96% and the average completion time was 2 s.

The performance of 4 classification models, namely LDA, Multi-Layer Perceptron (MLP), Self-Organized Map (SOM, unsupervised ANN) and Regulatory Feedback Networks (RFN, classification based on negative feedback) were compared [44]. Furthermore, the authors explored the possibility of multi-class classification, which means that a given pattern may belong to multiple classes. Six different classification setups were tested: Single, All Movements as Individual (AMI), Ago/Antagonist-Mixed (AAM), One-vs-All (OVA), One-vs-One (OVO) and All-And-One (AAO). Generally, they differ in the number of classifiers used, the strategy for classification and class definition (requiring mixed classes to be defined, or multi-class classification). For the 11 single-class patterns, which only have a single target class each, the offline accuracy was the highest for the LDA classifier using the OVO structure. The OVO structure relies on a multitude of classifiers that classify the pattern between two classes. The final output is set by majority voting on the combination of all classifiers. The second best result was obtained with the SOM-OVO structure, with 94.5% accuracy. Considering the problem with 27 pattern classes, which include multi-class samples, the highest accuracy achieved was 94.2% using the MLP-AMI structure. It was closely followed by a single SOM and LDA-AMI with a RR of 93.8% and 93.7%, respectively. The AMI structure uses a single classifier and requires the mixed classes to be considered separate classes, therefore increasing the number of outputs of the classifier.

The performance of a dimensionality reduction technique, the Non-negative Matrix Factorization (NMF), is presented in [55]. It was used to data mine the EMG signals and perform unsupervised learning using the RMS and the 4th order AR coefficients as features. The classifier used was an ANN. This method was studied on an existing dataset[1] that contains data from 2 EMG channels (extensor and flexor muscles) for 10 different finger movements (5 simple and 5 complex, involving one or more fingers moving). For the 5 single finger flexion classes, the attained classification accuracy was 93.92±0.63% (inter-subject). The 5 complex finger flexions were decoded accurately up to 87.58±0.36% of the samples.

Riillo *et al.* [15] presented a comparative study between supervised and unsupervised data pre-processing on healthy subjects and transradial amputees. The unsupervised PCA approach was compared to the common spatial pattern (CSP) supervised methodology. The PCs are calculated for the feature vectors, while the CSP methodology is used before feature extraction. The average accuracy for the PCA approach was 88.81%±6.58% using an ANN classifier and RMS-WA features, whereas the accuracy for the CSP strategy was slightly better, with 89.35%±6.16% using an ANN classifier, and M-RMS-WA as features. These results are valid for a set of 5 classes using 6 EMG channels. The amputee's classification accuracies were also relatively high, 92.04% for PCA and 93.4% for CSP. Seethanjali and Ray found that for their setup, simple logistic regression (SLR) fared better than other classifiers, such as decision trees, logistic model trees (LMT), ANNs, SVMs or LDA [63]. TD features allowed to achieve an accuracy of 93% for 6 classes.

[1] http://www.rami-khushaba.com/electromyogram-emg-repository.html

A spiking neural network (SNN) achieved an accuracy of 95.3% for 6 hand motions using 8 electrodes on the forearm [64]. For the development of the SNN, the study proposes the use of the NeuCube environment. The authors demonstrated that frequency-domain features do not represent the classes properly.

Stango *et al*. [23] studied the effect on recognition accuracy of problems such as electrode shift and channel loss. The classifier used was a SVM with a linear kernel with features retrieved from a variogram function. This resulted in 96% accuracy for 9 classes of gestures. When a longitudinal shift was simulated, it decreased to about 90%. A transversal shift caused a reduction to 80% without retraining. This technique is also accurate even when a large proportion of the EMG channels is omitted. Another study in which missing data are considered is presented in [65]. The authors propose the use of an extended full-dimensional GMM.

Rosati *et al.* [66] presented a hierarchical clustering-based method to group strides and by this way to characterize human gait from EMG data. Results show that the variability of the pattern onset/end timing is significantly reduced after clustering. Yamanoi *et al.* [67] proposed a myoelectric hand that estimates hand posture (8 grip postures) and grip force simultaneously. The ability to simultaneously estimate parameters is important for a number of EMG-based applications. EMG-based classification accuracy is critical for controlling forearm prosthetic devices. The effect of the temporal and spatial information was studied in the classification accuracy of 7 hand gestures recorded from partial-hand and trans-radial amputee volunteers, as well as able-bodied volunteers [68]. The authors concluded that the classification accuracy is significantly impacted by the number of electrodes and the signal processing window length. The optimal window size was also found to be independent of the number of electrodes used.

Table 2 summarizes the most recent studies in the field of EMG-based pattern recognition, showing for each study the number of classes considered, the number of EMG channels, the features extracted from the signals, the chosen classifier and the attained recognition accuracy.

D. NOVELTY DETECTION

The problem of novelty detection is important in order to improve the robustness of pattern recognition systems. Even if a system presents a relatively high accuracy in the classification of predetermined (trained) classes, it is still likely to miss-classify novel classes as one of the trained classes. This is a seldom addressed failure mode that could lead to unexpected results and potentially endanger users and their environment.

Liu and Huang [19] propose the use of an ensemble of one-class (OVA) SVDD classifiers that demonstrates a high level of generalization. If a new sample does not fall into any of the SVDD hyper-spheres, it is considered an outlier, a novelty. Else, it is considered a targeted pattern and can be further processed. However, this ensemble does not replace a multi-class classifier because the SVDD hyper-spheres may intersect. In this case, the same pattern is classified as multiple classes, so an extra step must be taken to determine the final classification output.

A different solution using modified boosted Random Forests (MCLPBoost) was studied to solve the problem of novelty detection [42]. The effect of arm movements on sEMG pattern recognition for hand and wrist motions was studied in [74]. Results showed that arm movements significantly impact classification performance when the classifier is trained in one arm condition and tested in another.

E. REGRESSION

Regression of EMG data is the process of predicting the motion of a biological joint using the sEMG signals from the muscles actuating that joint. sEMG signals may be affected by physiological and non-physiological factors. The accuracy of force estimation using sEMG is affected by changes in joint angle and contraction type, among others [75], [76]. An actual example of this effect is shown in [77]. Nine electrodes are placed over specific arm muscles (the most relevant for the actuation of the arm) and the movements are mapped to the EMG states using a linear model trained by an iterative prediction-error minimization algorithm.

Fleischer and Hommel [78] developed a torque-assistive knee exoskeleton in which the operator's intended torque is decoded from EMG signals. The control system requires models of the operator's body and exoskeleton, which use signals obtained from various sensors, thus requiring considerable calibration. A comparison between the ground truth torque and the produced torque on a stair climbing exercise can be seen on Fig. 5.

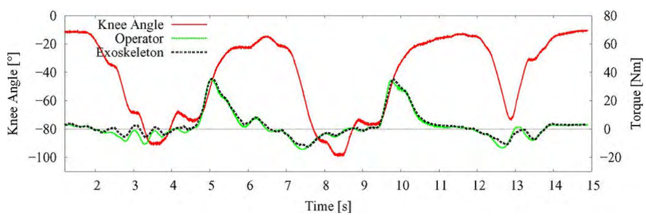

FIGURE 5. Torque produced (black) by a lower-limb exoskeleton system, adopted from [78]. The plot shows the operator's intended torque (green) and the knee angle (red), considering full torque support.

Haddad and Mirka [79] studied the effects of muscle fatigue on the EMG-force relationships. The authors present an algorithm to adjust the variable gain factor of the load estimator, as a function of the median frequency's negative shift measured on short term fatigue. Their work reduced the error caused by an invariant gain factor from 21.4% to 12.9%.

Hashemi *et al.* [80] use angle-based EMG amplitude calibration and parallel cascade identification (PCI) modeling to predict the nonlinear and dynamic relationship between EMG signals and force in dynamic contractions of the *biceps* and *triceps brachii* muscles. The authors achieved a minimum %RMSE of 8.3% for concentric contractions,

TABLE 2. Pattern recognition results using machine learning techniques in EMG data.

Authors	Classes/ EMG Channels	Features	Classifier(s)	Accuracy
Xiaorong Zhang *et al.*, 2013 [60]	3/4	MAV, ZC, WL, SSC	LDA	95.4% (99.7% after online retraining)
Matsubara and Morimoto, 2013 [41]	5/4	RMS	SVM	73±13%
Al-Timemy *et al.*, 2013 [61]	15/6	6AR, RMS, WL, ZC, IAV, SSC	OFNDA (reduction) LDA (classifier)	98.0%
J. Liu and Zhou, 2013 [20]	7/57	TD, 6AR, RMS	LDA, KNN	97-98%
Z. Li *et al.*, 2013 [42]	7/6	MAV, ZC, SSC, WL	Boosted Random Forests (with rejection of untrained classes)	92%/20% (trained/novel) or 80%/80%
Phinyomark *et al.*, 2014 [28]	8/4	dAR	QDA	97.96±1.1%
Pan *et al.*, 2014 [69]	7/7	MAV, ZC, WL, SSC	LDA	95.64%
Riillo *et al.*, 2014 [15]	5/6	M, RMS, WA, SSC	PCA (reduction) ANN (classifier)	88.85±7.19%
Ju and Liu, 2014 [43]	10/5	RMS	FGMM	92.75%
Tkach *et al.*, 2014 [32][a]	(9-13-17-29) /(14-15)	6AR, MAV, ZC, SSC, WL	LDA	97.5% (9 classes) 92.0% (13 classes) 88.8% (17 classes) 81.0% (29 classes)
Ortiz-catalan *et al.*, 2014 [44]	11/4 or 27/8	MAV, ZC, SSC, WL	LDA, MLP, SOM, RFN	11 classes: 95.7% (LDA-OVO)27 classes: 94.2% (MLP-AMI) 93.8% (SOM)
Naik and Nguyen, 2014 [55]	5/2	4AR, RMS	NMF (reduction) ANN (classifier)	93.92±0.63% (single finger) 87.58±0.36% (two fingers)
Li *et al.*, 2014 [70]	4/4	4AR	ANN	93.0%
Purushothaman and Ray, 2014 [71]	6/4	MAV, ZC, SSC, WL	SLR	91.1%
Amatanon, 2014 [72]	10/8	MAV or MV	ANN	94.7±4.6% (MV) 97.9±1.5% (MAV)
Kawasaki *et al.*, 2014 [45]	4/6	WL	ANN	For 4 patterns an average RMS error of 0.164 (joint angles)
Tsai *et al.*, 2015 [46]	4/6	STFT-ranking	PCA (reduction) SVM (classifier)	93.9±4.3%
Peng *et al.*, 2015 [64]	6/8	MAV, WL	NeuCube SNN	95.3%
Liu *et al.*, 2015 [49]	11/4	6AR	FDA	91.2%
Paleari *et al.*, 2015 [73]	11/192	RMS	ANN	96.5%
Stango *et al.*, 2015 [23]	9/48	Variogram	SVM	95.8±2.3%

[a]The subjects were previously subjected to a TMR procedure.

10.3% for eccentric contractions and 33.3% for fully dynamic contractions.

In order to estimate the force generated by muscles, Li *et al.* [21] use a high-pass filter to remove most of the signal components in the low-frequency range, rectify the signal and calculate the signal envelope. Considering further processing steps, the methodology achieved a good estimation of the resulting force on the joint. An alternative method based on pattern classification uses sliding windows of 100 time steps (10 Hz) with 2 features per channel (MAV and WL). The minimum %RMSE obtained was 6.9% on the *biceps brachii*. The authors also found that for a natural control of their exoskeleton application, the delay between the onset of the muscle contraction and the corresponding motion of the device must not exceed 300 ms. Another study showed that a non-parametric machine learning model obtained by Gaussian Process Regression (GPR) modeled the elbow torque better than a pneumatic artificial muscle (PAM) model [81]. EMG signals were obtained from the *biceps* and *triceps*. Recently, Valentini *et al.* [82] used a GMM to estimate the angle of a human joint with wavelet transform features obtained from sEMG signals. Their system achieved real-time performance with a processing time below 3 ms. The same problem has been tackled with recurrent neural networks (RNN), namely a nonlinear auto-regressive exogenous (NARX) model [83]. In [84], a time-delay neural network (TDNN) was used to predict the elbow's torque in dynamic conditions using only sEMG data. The test data showed a root mean square error of 1.0 Nm in a range of around ±14.0 Nm.

A signal normalization approach proposed by Han *et al.* demonstrated a significant reduction of the dependence on varying external loads [85]. Their system estimated joint movement continuously from EMG signals using a state-space Hill-based muscle model closed-loop approach. Other authors studied the effect of varying loads on joint angle estimation and proposed different alternatives to overcome the classification problems those loads may bring [86].

In [87], Krasoulis *et al.* propose a method to obtain finger movement for SPC using linear and kernel ridge regression (KRR) from sEMG and accelerometer data. The results showed that the correlation was $R^2 = 0.79$ for KRR. The authors also found that non-linear regression may outperform linear regression during within-movement generalization. Their performance is comparable when generalizing to novel movements.

F. MULTI-MODAL SENSING

Ju and Liu [43] use 3 types of sensors to capture simultaneously the finger angle trajectories, the hand contact forces, and the forearm EMG signals. They establish correlations between the sensors' signals by using Empirical Copula. Chang *et al.* [88] propose the combination of EMG sensors with an IMU to improve the accuracy of hand gesture recognition. The authors report a RR of 97.5% for 6 classes of gestures which were performed by 10 subjects. A SVM with a linear kernel provided the best results.

A device with a wrist-worn motion sensor (IMU) and 4 sEMG sensors achieved a RR of 95.9% for 40 distinct signs of the American Sign Language with an SVM classification model [89]. Nevertheless, most of the features were obtained from the inertial sensors, which explains the relatively high RR considering the large amount of distinct gestures.

IV. APPLICATIONS

EMG signals have been used in different applications, namely for rehabilitation, prostheses control, medical diagnosis and for the most diverse human-machine interaction approaches. However, most of these applications are confined to controlled laboratory environments and do not have yet the required level of reliability for deployment in the real world. Research in EMG-based devices will proceed in the coming years towards the improvement of EMG pattern classification in multi-user systems and reduction of the effect of real-world issues, such as electrode shift and presence of novel patterns. Additionally, prosthesis control must be extended to more complex tasks in order to reduce the prosthesis rejection rates and allow the intuitive control of machines. Furthermore, the the combination of EMG data with other sensors appears to improve substantially the robustness of classification systems.

Farina *et al.* [8] have previously presented a thorough review on upper-limb prostheses, including previously studied control strategies and the challenges for future studies. They also present a list of ideal characteristics of a EMG-based control system for upper limb prostheses. Although sEMG control has been studied for over 60 years, so far there has not been a significant evolution on clinical and commercial upper limb prostheses. Current systems are robust, but they are not very natural nor practical, so they are often abandoned by their users. Today's control techniques rely on direct control (DC), in which the user has to elevate the EMG signal above a predetermined threshold to generate a command (controlling a single DOF in one direction). If a patient intends to control multiple DOFs, the DOF combination must have been predefined, or the patient has to select and control each DOF individually. Some researchers are currently exploring the use of pattern recognition for the simultaneous control of several DOFs, as described in section III-C.

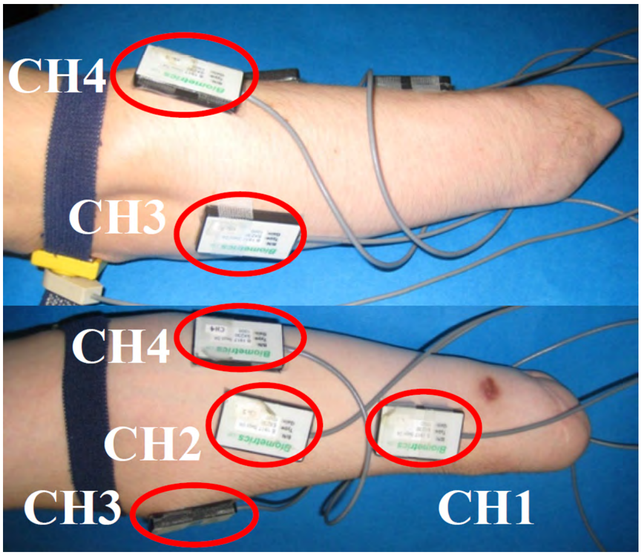

FIGURE 6. Electrode positioning in forearm amputee, adopted from [45].

An architecture for the control of a UB Hand IV device is presented in [90]. Tele-operation is performed using 8 sEMG channels. Performance was measured on grasping tasks and a high success rate was achieved. A prosthetic hand is controlled by forearm amputees using regression models for the hand joints' angles (fingers, wrist and palmar angles) from sEMG data [45]. The system was successfully tested by a right forearm amputee using a set of 4 hand patterns, Fig. 6. Recently, EMG has been used to predict the intended movements of an upper limb amputee for prosthesis control [91]. The proposed methodology demonstrated to be robust to the negative effect of untrained actions such as limb position changes.

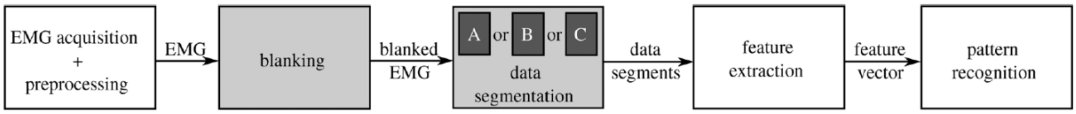

FIGURE 7. Signal processing chain including blanking, adopted from [92].

Lower-limb prosthesis control is not studied as often as upper-limb protheses. Nevertheless, a reference study presents a lower-limb DAQ system in which the EMG signal is used to predict gait mode change of a leg [94].

In the conventional DC method for prostheses, each EMG signal is analyzed independently and concurrently to match the number of DOFs to be controlled. In this scenario, each EMG channel is used as the unique control signal for each actuator and the range of actuation is controlled proportionally using the amplitude or RMS of the EMG signal [8]. This means that only one function can be used at a time. However, it is possible to create a control system in which multiple functions are directly controlled, simultaneously and proportionally (SPC), without the need for a switching function. This type of control may be improved by the use of a Bayesian filter on sEMG data [95].

Novel control methods based on PR assume that when a given subject tries to perform a certain task, there is a consistent EMG pattern in a group of electrodes. Using these methods, the subject is not required to switch between DOFs in order to perform a task, as necessary in DC systems. Nevertheless, this type of approach does not allow the simultaneous control of more than one motion, a characteristic of natural movements. Research in PR shows high classification accuracy for large sets of motions, but there are still no commercial/clinical systems exploiting PR-based control. Even in the presence of high accuracy, a small amount of repeatable errors may be unacceptable in some tasks. A classification error may lead to an unwanted motion that could compromise the entire functionality of the system. Furthermore, the control is still sequential, controlling only one type of motion at a time.

Based on PR, Ortiz-catalan *et al.* [44] have been trying to interpret combined motions as new classes. This may become unfeasible as the number of elementary motions increases, since the number of classes would grow exponentially. Alternatively, there have been approaches based on regression control of joint kinematics with EMG. This requires modeling the relationships between forces and kinematics, which are difficult to determine. The coefficient of determination has been ascertained to be in the range of 70% to 90%, when comparing ANNs, linear regression and kernel methods. Unsupervised methods can also provide a solution to this problem, such as signal factorization and NMF [55]. The motion accuracy in control tests between different approaches have been shown to be similar, since the users are often capable of learning how to adapt their muscle contractions to improve motion RR.

Scheme *et al.* [96] introduced two new proportional control algorithms based on PR control. In their work, the classifier output is used to determine movement direction, while the proportional control (PC) gain is computed with other metrics. The traditional approach is based on mapping linearly the EMG amplitude (using the MAV with a class-specific gain) to the force or speed to be generated by the actuators. If multiple sensors are used, a summation and normalization of the MAV of all channels is performed, with equal weights. Their first approach takes into account the intra-class and intra-channel averages. Also, the PC-EMG gain is square-mapped, so that the PC has better resolution at lower speeds. The other approach is expressed in terms of a percentage of the maximum contraction and it is mapped cubically. In either case, the data needed to create the PC model are limited to a small training data set. The authors concluded that this last method presented better results in terms of usability for both able bodied subjects and amputees when combined with a PR system.

Ison *et al.* [35] developed a 4-DOF EMG SPC control interface for a 7-DOF manipulator using a high density array of sEMG electrodes. They also circumvented the necessity of narrow electrode placement constraints with signal decomposition inspired by natural muscle synergies. Succinctly, muscle synergies are visible when 2 activation signals control a single joint DOF, each one in a different direction. A formulation proposing the use of task-specific muscle synergy activation coefficients is shown in [97]. The coefficients are modeled as the latent system state and estimated using a constrained Kalman filter. The accuracy in task discrimination is around 90% and it is computationally efficient (decision reached in under 3 ms).

In order to restore the performance of pattern recognition in prosthesis control when EMG signals are corrupted by electrical stimulation artifacts (due to electrocutaneous stimulation feedback provided to the user by the prosthetic system), researchers investigated artifact blanking with three data segmentation approaches, following the signal processing chain displayed in Fig. 7. Basically, the blanking block in Fig. 7 removes stimulation segments from the raw signal, so that the samples used for feature extraction are free of signal interference. The results demonstrated that the proposed artifact blanking method can be used as a practical solution to eliminate the negative influence of the stimulation artifact on EMG pattern classification [92].

Neuromuscular diseases can be diagnosed using EMG signals [98]. This is achieved by the decomposition of the signals into frequency sub-bands using the discrete wavelet transform (DWT), and classified using a SVM model whose parameters were determined by particle swarm optimization (PSO). The system yielded an overall accuracy of 97.41% on 1200 signal sets. Research has been carried out to improve the motor control of patients who have had central nervous system (CNS) injuries that caused degraded CNS-Motor signals [99]. Several disorders of the muscular system may be diagnosed using EMG signals, such as dystonic muscles [100]. PR on EMG signals has also been recently used to improve electro-larynx performance on patients who lost their voice-box, usually due to larynx cancer. Using 2 EMG channels positioned over neck muscles, researchers tried to decode the intended voice sound patterns, using either SVM PR or SVM regression on 4 distinct classes. The regression achieved 33% lower RMSE than the classification, but subjectively, the classification provides a more accurate representation of the patient's intention. The accuracy rate achieved was 78.05±6.3% [101].

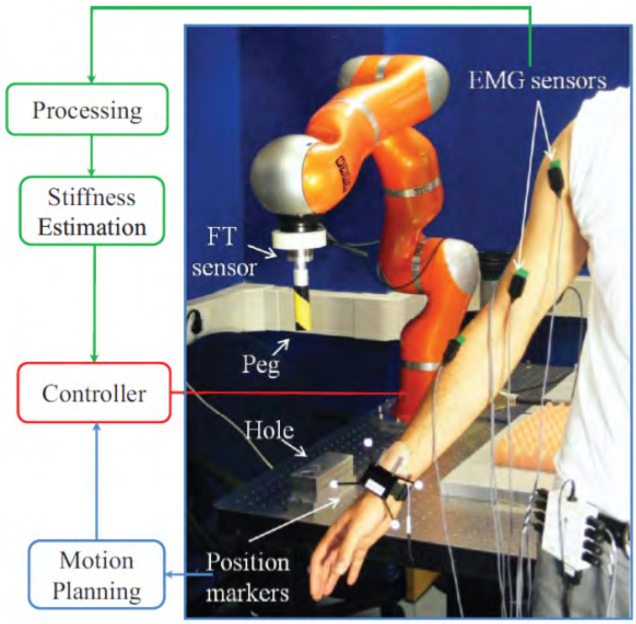

FIGURE 8. Diagram of a data acquisition system used to estimate the joint stiffness to be replicated by a robot during a tele-operation session, adopted from [93].

In an interesting study, the stiffness command to a robot was derived in real-time from the measurement of 8 EMG channels from an operator's arm, Fig. 8, [93].

V. CONCLUSION

Although current research on EMG-based control is targeted mostly for upper-limb prostheses through the application of EMG sensors on the forearm, there is a need for the development of sophisticated EMG-based human-machine interfaces. Robust PR on the forearm's EMG signals may create a strong alternative to hand gesture recognition from vision systems or data gloves. The current solutions are either too restrictive and unreliable (vision) or cumbrous to use (gloves). A forearm band with dry sEMG and inertial sensors would be a good solution for discrete hand gesture classification.

The current efforts on EMG PR development are targeted at increasing the reliability of the classification by anticipating and correcting sources of EMG disturbance, such as muscle fatigue, varying skin impedance, electrode shift and liftoff. The solutions studied are based on (1) the use of HD-EMG monopole electrode arrays to obtain topographical maps of muscle activity, (2) further signal conditioning, (3) and increased robustness of the classification models. The use of electrode arrays greatly increases the number of signal channels. In turn, this requires the use of dimensionality reduction strategies and smart feature selection (or deep learning), since high-dimensional input features require much higher computation power to train and use classifiers, thus undesirably increasing the time between signal acquisition and classification. On the other hand, these high-dimensional spaces have the potential to be more robust to imprecise electrode placement and electrode shift. Some studies have showed their potential to detect muscle activation synergies.

Classification accuracy is still very dependent on the feature-classifier combination. The features selected are very often time-domain features and AR model coefficients. Novel features include variogram-based and STFT features. The classifier models most commonly used are LDA and its variations, SVM and ANN in several forms. Joint angle/torque regression based on machine learning is being developed with RNN, PCI, GPR, GMM and KRR. All these methods are being used on single muscle-actuation with relative success and will possibly be used in the upcoming HMI interfaces.

An important element that is lacking discussion in most studies in this domain is the reproducibility of the presented experiments. The data sets are seldom published, making it difficult to compare different methodologies. Furthermore, it is challenging for different researchers to reproduce exactly the same data acquisition setup, due to the limited availability of the instrumentation (many researchers use custom-build sensors) and high sensibility of the EMG sensors in respect to the electrode placement conditions. We believe that in the future, setups with dry electrodes will prevail because of their ease of use. Furthermore, larger data sets should be built around reproducibility.

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