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Topical Review

The role of muscle synergies in myoelectric control: trends and challenges for simultaneous multifunction control

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Abstract

Myoelectric control is filled with potential to significantly change human–robot interaction due to the ability to non-invasively measure human motion intent. However, current control schemes have struggled to achieve the robust performance that is necessary for use in commercial applications. As demands in myoelectric control trend toward simultaneous multifunctional control, multi-muscle coordinations, or synergies, play larger roles in the success of the control scheme. Detecting and refining patterns in muscle activations robust to the high variance and transient changes associated with surface electromyography is essential for efficient, user-friendly control. This article reviews the role of muscle synergies in myoelectric control schemes by dissecting each component of the scheme with respect to associated challenges for achieving robust simultaneous control of myoelectric interfaces. Electromyography recording details, signal feature extraction, pattern recognition and motor learning based control schemes are considered, and future directions are proposed as steps toward fulfilling the potential of myoelectric control in clinically and commercially viable applications.

Keywords: muscle synergies, brain-machine interfaces, EMG

1. Introduction

Myoelectric control first gained attention as a potential control mechanism as early as the 1940s [1]. With control inputs non-invasively representing nearby motor unit action potentials (MUAPs) through surface electromyography (sEMG), myoelectric control research has been primarily driven by the potential to create prostheses and orthoses which intuitively respond to users' intentions [2, 3]. As robotics research trends toward compliant manipulation and multimodal feedback [4–8], these controls also show promise for select applications in robot teleoperation [9–18] and other human–machine interfaces [19–24]. However, despite a constant research focus and increasing desire for enhanced myoelectric control applications, research advances have struggled to translate to clinical and commercial applications [3, 25–27].

For example, the first myoelectric prostheses were introduced in the 1960s [28, 29] and 1970s [30, 31], and widely available prostheses today generally use the same direct control approach: using two independent muscles or weak and strong contractions of a single muscle to control a single degree of freedom (DOF), in conjunction with switching techniques such as co-contraction, a mechanical switch or force-sensitive resistors to control multiple joints [32, 33]. Although users desire simultaneous, multifunctional control of prostheses, they often reject myoelectric prostheses in favor of more robust body powered ones [32, 33]. The lack of reliable simultaneous control schemes is one of the major reasons for a gap between research and commercial applications [33, 34]. Similarly, advanced applications of exoskeletons, teleoperation, and human–machine interfaces all require reliable simultaneous control of multiple DOFs, and have struggled to provide commercial applications [26].

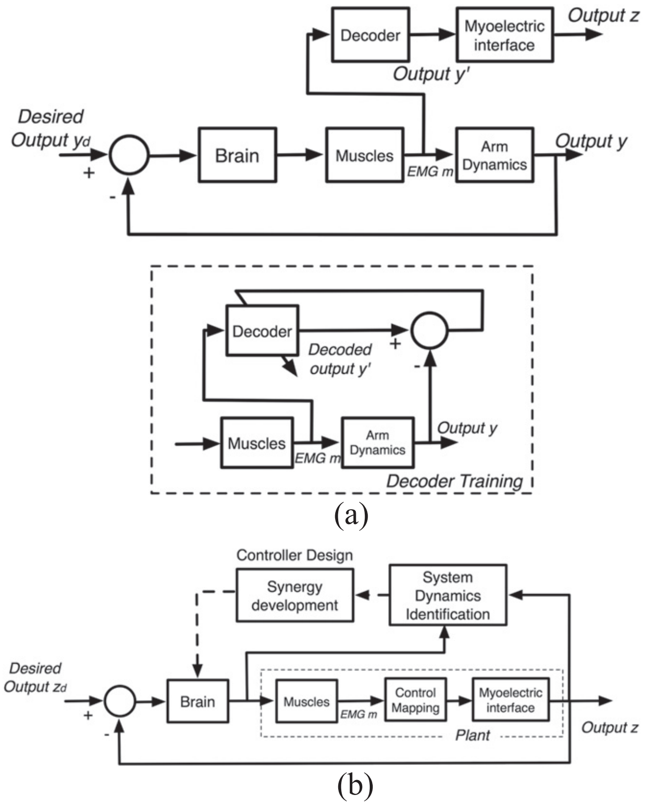

Figure 1. General models of myoelectric interface interaction. (a) Interfaces with trained decoders. A decoder is trained to map sEMG signals (m) to arm dynamics (y). Once trained, the decoder is used in real-time to estimate arm dynamics (y') and map it to output (z) for an interface. (b) Interfaces utilizing motor learning. The brain learns a model of the plant to be controlled (system dynamics identification) by comparing motor commands and output (z) of the interface. New synergies are developed through controller design based on the system identified, which are then utilized while adjusting motor commands.

Simultaneous myoelectric control, in which multiple DOFs can be controlled at the same time via sEMG inputs, requires identification of complex interactions between multiple muscles, commonly referred to as muscle synergies [35–39]. Specific to myoelectric control and as used throughout this paper, *muscle synergies* are defined by these complex muscle activation patterns, which are executed by users as high-level control inputs, regardless of any neurological origin [40–47]. Linear combinations of synergies are capable of describing complex force and motion patterns in reduced dimensions [48–51]. Thus, robust representations of synergies within a multifunctional control scheme contribute to reliable processing and robust outputs consistent with a user's intent. Control schemes associating synergies with control outputs can generally be grouped into two approaches: pattern recognition and motor learning.

Pattern recognition-based controls decode muscle activity into intuitive control outputs by training a model on a dataset associating sEMG-related inputs with desired outputs, as seen in figure 1(a). The models are trained via pattern recognition techniques to mimic intent based on existing synergies.

Motor learning-based controls train a motor system to develop and refine synergies associated with system dynamics of a specific mapping function relating sEMG inputs with control outputs, as seen in figure 1(b). The user learns the system dynamics via feedback while interacting with the control interface.

Many myoelectric control systems have been proposed over the last half century [3, 27, 52], particularly for prostheses [32, 53–55], and exoskeletons [26]. Those providing simultaneous control have demonstrated enhanced performance during real-time control [56–58]. However, due to complexities associated with sEMG recording [59, 60], wide inter- and intra-user variability in detectable muscle synergies [25, 61], and general nonlinear properties of sEMG signals [62], most proposed control schemes have struggled to provide robust and reliable systems. Moreover, muscle synergies have only recently been recognized as influential components in control schemes [40, 50, 51, 63], and few techniques explicitly utilize them in the scheme [41–45, 47–49].

The purpose of this article is to describe the role of muscle synergies in state-of-the-art myoelectric control schemes and present challenges and opportunities for achieving robust simultaneous control with clinical and commercial merit. Section 2 addresses the unique challenges associated with muscle synergies and sEMG processing which may influence usability of control schemes. Section 3 evaluates methods for robust feature extraction and synergy representation from raw sEMG signals. Sections 4 and 5 assess pattern recognition- and motor learning-based control schemes, respectively, in terms of their potential to provide reliable simultaneous control given proper feature inputs. Section 6 presents future directions in myoelectric control aimed at overcoming the defined challenges to obtain user-friendly, simultaneous control of multiple DOFs in myoelectric applications. Finally, section 7 concludes the review by summarizing the main points to consider while developing new control strategies.

2. Muscle synergies via sEMG

Muscle synergies are studied extensively in neurophysiology as a potential basis for neural control. Multiple studies support the hypothesis that the human motor system directly initiates movement through flexible combinations of muscle synergies [64–69]. Other studies interpret these patterns as task and biomechanical constraints rather than direct synergies [63, 70, 71]. There is an ongoing debate between the two theories [72], and perceived muscle synergies cannot currently be proven or disproven to have a neural origin [73]. Regardless of neurological origin, muscle synergies are influential in myoelectric control schemes due to sEMG inputs directly encoding muscle activation timing, shape and intensity [61].

The imperfect ability to consistently measure muscle activations with sEMG has been well documented [59]. Factors such as muscle depth and thickness, innervation zones, quality of skin contact, skin impedance, timing and

Table 1. Factors influencing muscle synergies in myoelectric control.

Factor	Cause	Main Effect	Potential Solutions
Electrode placement	Spatial variability (e.g. proximity to innervation zone [75], muscle fiber heterogeneity [76, 77], cross-talk [27])	Variable SNR [75, 78, 79], amplitude [59, 80, 81], electromechanical delay [82–84]	Consistent placement [59, 74], large electrodes [85], multiple electrodes per muscle [75, 80, 86]
Cross-talk	Contamination by nearby muscle activity, electrophysiological signals and external noise [59, 87]	Exaggerate positive muscle correlations [87], add irrelevant signal variability [59, 61]	Record muscle belly [75], double differential electrodes [87], reduce skin–electrode impedance [86], strategic filtering [87–92]
Amplitude cancellation	MUAP phase differences [93], high contraction levels [94]	Uncertainty in absolute sEMG activity level [61]	MVC [95], synergies via onset timing and sEMG shape [96]
Muscle selection	Undetected muscle variance [40], biomechanical constraints [42, 97]	Incomplete synergy sets [40], loss of precision control [51, 98]	More muscles, dominant muscles from known synergies, major muscles [40]

intensity of muscle contractions, and cross-talk from nearby muscles all add variability to sEMG recordings [60]. When recording from multiple muscles to extract synergies, many of these complications are magnified. In addition to traditional concerns for robustness due to transient changes in sEMG signals (e.g. electromagnetic interference, skin perspiration, electrode shift and fatigue) [25, 74], control schemes implementing simultaneous multifunctional control require extra consideration with respect to electrode placement, potential cross-talk, amplitude cancellation [61], and the number and selection of muscles [40]. These factors are summarized in table 1.

2.1. Electrode placement

Electrode placement influences signal-to-noise ratio (SNR) and amplitude due to the spatial variability of muscle activity [27, 59, 75–80, 82–84]. When targeting specific muscles, ideal placement is close to the muscle belly away from innervation zones [99]. However, external forces and changing postures shift electrodes relative to underlying muscles during use [25]. Consistent placement between sessions, both absolutely within and relatively between subjects, makes these effects less significant [59, 74]. Large electrodes and/or multiple recording sites per muscle may also reduce the effects and extract robust signals without requiring ideal placement [75, 80, 81, 85, 86].

2.2. Cross-talk

Cross-talk contributes to exaggerated muscle synergies and unnecessary variability when performing tasks [27, 59, 61, 87]. Although the effects can be reduced [75, 86, 87], identifying cross-talk may add useful information from small or deep muscles that cannot be recorded directly [25]. Independent component analysis (ICA) [88] and spatio-temporal filters [89–92] are capable of extracting individual muscle activities from sEMG signals to separate cross-talk as well as any interference from other electrophysiological signals [100].

2.3. Amplitude cancellation

Amplitude cancellation increases at higher activation levels, underestimating the sEMG activity up to 50% at maximal contraction [94]. Normalizing signals via maximum voluntary contraction (MVC) [101] reduces this effect, but typically causes overestimation at intermediate activations [95]. However, amplitude cancellation has little effect on onset detection, often preserving muscle activation timing and shape of sEMG patterns to cause minimal impact on detected synergies (see section 3.2) [61, 96].

2.4. Muscle selection

Muscle selection also directly impacts control via muscle synergies [40, 42, 97]. Smaller sets of muscles often overestimate explained variance, forming incomplete synergy sets and threatening precision controls [51, 98]. Increasing the number of muscles, selecting dominant muscles from a master set of synergies, or approximating dominant muscles with major muscles can each help maximize precision [40].

Extracting more information through multiple sEMG sites assists with each of the above challenges to effectively characterize natural synergistic muscle behavior [25]. This information can generally be described by linear combinations of muscle synergies which form complex mappings between the synergy and its effect on a limb [51]. Thus, feature extraction from incoming signals is essential to provide descriptive synergistic inputs to a control scheme depicting these mappings.

3. Feature extraction

Ideal feature extraction converts a set of incoming sEMG signals into distinguishable and repeatable descriptors, such as synergies, while discarding irrelevant information. The choice of features is often more influential than the choice of control scheme for achieving efficient performance with multifunctional controls [102, 103]. For instance, features capturing low-intensity, low-frequency components of

Table 2. Feature extraction influence on myoelectric control.

Domain	Example features	Advantages	Challenges
	EMG Features		
Time	Linear envelope [62], mean absolute value, root mean square [108], zero crossings, slope sign changes, waveform length [106], wave complexity [74], Willison amplitude [109], log-detector [110], histogram [104]	Computational simplicity [74], direct relationship to contraction level and force [3, 111]	Sensitive to noise [3, 61], transient sEMG changes [25, 112], amplitude cancellation [111]
Frequency	Power spectral moments [113], power spectral density [23], spectral magnitude averages [107], short time Fourier transform, median frequency [11], cepstrum [114], short time Thompson transform [107]	Fatigue detection [115], distinguish non-stationary signals [113]	Computational complexity, poor time resolution [113], spectral leakage, high variance [3]
Time–frequency	Wavelet packet transform [116–118], discrete wavelet transform [24, 119]	Time and frequency resolution [102], transient and static representation [116]	Abstract features, high-dimensional outputs, many design parameters
	Synergy Features		
Feature projection	NMF [49], PCA [12], ICA, fuzzy clustering [120], LDA, orthogonal fuzzy neighborhood discriminant analysis [121], self organizing feature maps,	Dimensionality reduction, efficient computation [122], robust to electrode shift [49]	Information loss, requires extra calibration [45]
Spatial filtering	Common spatio-spectral pattern [123], multiresolution muscle synergy analysis [124]	Sparse domain, user-independent patterns [124]	Computational complexity, high-dimensional

composite sEMG may capture contributions from deep muscles, which offers more functionality (or noise) compared to feature sets removing this information [25]. Moreover, Berniker *et al* [50] show that linear controllers based on synergy inputs are capable of similar performance to full-dimensional nonlinear controllers. Accordingly, feature evaluation focuses on clustering within and discrimination between tasks [104, 105].

Hudgins *et al* [106] established the first benchmark for highly discriminant control schemes using a set of features based on simple time domain statistics to distinguish transient patterns in a single sEMG channel. Since then, many extraction techniques have been proposed to separate more complex, multi-channel systems in which Hudgins' features struggled [107]. These techniques follow two approaches (see table 2).

1. *EMG features* extract structural characteristics from a single sEMG channel to describe the specific signal.
2. *Synergy features* extract information from multiple channels simultaneously to provide cross-channel patterns and context about underlying muscle synergies.

3.1. EMG features

EMG features extract structural characteristics from each channel individually. These features are categorized into their respective domains of time, frequency and time–frequency. Each domain has been extensively described in previous works [3, 125, 126]. They are simply reviewed here in terms of overall influence on simultaneous control schemes.

3.1.1. Time domain. Time domain features are based on signal amplitude, proportional to number and rate of activation of motor units [3]. A few time domain features, such as zero crossings and slope sign changes, give measures closely related to the frequency domain features discussed below. Most others indicate signal energy, activation level, duration of contraction and a relationship to force output [111]. Pattern recognition-based control schemes often employ variations of Hudgins' original set [127–134], while motor-learning schemes compute the linear envelope (full wave rectification and low-pass filtering) for each sEMG channel [47, 58, 61, 135–137].

However, the features are sensitive to amplitude cancellation and noise from the stochastic sEMG signals [25, 61, 111]. Changing contraction levels are managed by either retraining control schemes [74] or recalibrating MVC [61] each session. Noise sensitivity is reduced by computing features over a segmented window of data [3] or after smoothing the signal with a filter [61]. In both cases, the variance is reduced at the expense of increasing bias and delay in the system, altering the synergies detected and used in the control scheme. Smith *et al* [138] suggest a window length of 150–250ms, and Kamen and Gabriel [139] suggest a low-pass filter retaining 95% of the total power of sEMG as a tradeoff between robust features and minimal delay. Adaptive filters attempt to completely remove delay using varying time constants [140] or Bayesian probabilities [141] at the expense of additional complexity. As an alternative to windowing and filtering, signal whitening and processing multi-channel signals can help reduce the variance of time domain features without increasing the bias [108, 142]. Thus, autoregressive coefficients [143], and multivariate autoregressive models [144] are often useful additions to time domain feature sets [56, 103, 128, 145–147].

Due to the non-Gaussian properties commonly associated with sEMG signals [148–150], higher order statistics [151–153] and information theory measures such as entropy [154] have also been proposed. Although good separators for isometric contractions, they are less reliable in dynamic environments and their computational complexity currently restricts any real-time applications [111].

3.1.2. Frequency domain. Frequency domain features provide information about the rate and shape of MUAPs [11, 107, 113–115, 155–157]. Sliding windows incorporate time into the frequency descriptors to describe non-stationary signals, but the commonly used Hamming window destroys energy information at the beginning and end of each segment [107]. The window size also adds a tradeoff between time and frequency resolution in the descriptors. In addition, a comparison between frequency and time domain features by Du *et al* [107] found that the increased computational costs of spectral features do not significantly increase classifier performance over select time domain features. However, Khushaba *et al* [113] recently proposed a set of frequency features describing robust power spectrum characteristics which can be efficiently computed in the time domain. This set shows promise for use in future myoelectric control schemes.

3.1.3. Time–frequency domain. Time–frequency features represent transient as well as steady state patterns from dynamic contractions [24, 102, 116–119, 158–161]. Multiresolution analysis with wavelets transforms signals to a high-dimensional sparse domain, revealing characteristics that most other extraction techniques miss [3]. Synergistic patterns between sEMG channels are also more likely to be significant than data represented in the above dense domains.

Time–frequency features significantly outperform other feature sets when separating data from dynamic movements [116, 147, 162, 163]. However, the high dimensional domain, abstract features and computational complexity may exclude time–frequency features as an option for some applications. Moreover, the choice of wavelet and partitioning has a dramatic effect on the resulting features. Thus, this domain is rarely used in control schemes.

3.2. Synergy features

Synergy features extract information from multiple sEMG channels simultaneously to depict time-invariant synergies representing underlying muscle coordination principles while performing various tasks [122, 164]. Different sEMG patterns are then described by different numbers and composition of synergies [67, 165]. By identifying relative activations between synergistic muscles, synergy features are inherently robust to amplitude cancellation and include both bio-mechanical constraints as well as patterns from different joints in order to reduce control complexity [46]. Thus, linear combinations of synergy features form complex outputs capable of performance similar to nonlinear models [50, 51]. As more channels are used to collect sEMG information, these features help separate robust synergies from variant muscle activity. Methods for extracting synergy features include feature projection [122] and spatial filtering [166].

3.2.1. Feature projection. Feature projection techniques transform a multi-channel input space into a lower-dimensional subspace reflecting basic coordination principles between channels. These methods portray the linear instantaneous mixtures of sEMG commonly associated with muscle synergies [49]. Tresch *et al* [164] evaluate different projection techniques in terms of representing robust synergies. Pure synergies are most common, extracted by transforming raw or linear enveloped sEMG channels [122], but abstract representations have also been formed by projecting other feature sets to lower dimensions [116], reducing the feature space for more robust inputs to the control scheme. However, the projection loses information, so synergies must be distinguished from irrelevant information (see section 2).

(a) Non-negative matrix factorization. Non-negative matrix factorization (NMF) is the most common and expressive technique for extracting time-invariant synergies [122, 164]. NMF prescribes a synergy subspace restricting expressible data points to combinations of each non-orthogonal component [122]. It is commonly used as a descriptive measure of specific time-invariant muscle synergies [40, 46, 51, 63, 167–169] due to relaxed constraints on orthogonality and statistical independence between each component and relative robustness to noisy data [164]. Ajiboye *et al* [41] show that NMF can also be used as a predictive measure for motions and configurations. Most recently, NMF is used to directly control 2-DOF and 3-DOF simultaneous proportional controls via linear synergy combinations [43–45, 48, 49].

(b) Principal component analysis. Principal component analysis (PCA) describes the major orthonormal activation patterns without imposing restrictions within the space defined by these components [36, 122, 170, 171]. With orthogonality constraints between components, PCA describes a synergy space better than specific synergy components [172, 173], which has shown useful for simultaneous control schemes. Artemiadis *et al* use PCA to transform seven [174] and nine [12] channels to two-dimensional synergy planes for simultaneous control of an anthropomorphic robot arm along a plane and in three dimensions respectively. Muceli *et al* [175] applied PCA to control a 4-DOF wrist/hand with more comprehensive and lower-dimensional synergy inputs.Yatsenko *et al* [176] use a variation of PCA to detect orthonormalized principal bases for a set of contractions to provide an orientation for simultaneous control outputs. Hargrove *et al* [177] extract

task-specific synergies with individual PCA from untargeted muscles susceptible to cross-talk, resulting in significantly reduced classification errors.

Before synergies were widely recognized in myoelectric control, Englehart *et al* [102] compared the performance of PCA on different sEMG feature sets (Hudgins' original time domain (HTD) [106], short time Fourier transform, discrete wavelet transform (DWT), and wavelet packet transform (WPT)) to discriminate between 2-DOF in the arm. While PCA and WPT gave the best performance, applying PCA on HTD significantly improved performance over the original HTD set, demonstrating the advantages of transforming single channel feature data into abstract synergy spaces. Nielsen *et al* [178] perform a similar analysis with simultaneous control, reaching the same beneficial conclusion. Other control schemes create abstract synergies from DWT [160] and spectral features [23] for more robust classifiers.

(c) Independent component analysis. ICA projects statistically independent muscle synergies from multiple sEMG channels [164, 179, 180]. It is particularly useful to identify subject-independent synergies dominated by a single muscle [41] to eliminate cross-talk [88] and interference from other electrophysiological signals [100]. Naik *et al* [181] use ICA to identify static synergies associated with six hand gestures.

(d) Linear discriminant analysis. Linear discriminant analysis (LDA) projects data into task-specific synergies which maximize between-task variance, whereas unsupervised projections may merge tasks utilizing similar synergies. This effect is seen in [177] when comparing supervised and unsupervised PCA. Chen *et al* [152] project five distinct sEMG feature sets to an abstract task-specific synergy domain separating nine wrist motions. Although this space can be used directly for simultaneous control inputs, LDA is typically used in its classifier form to predict outputs in a control scheme (see section 4.1.1).

(e) Clustering. Clustering methods depict muscle synergies as groups of related muscle activations. Ajiboye *et al* [120] use fuzzy C-means, and Kurlik *et al* [143] use fuzzy neural networks to cluster sEMG data into common muscle activities. However, the clusters are based on Euclidean distance and assume Gaussian distributions. As more channels are included as inputs, the curse of dimensionality makes clustering less robust as the distributions become less Gaussian.

(f) Nonlinear projections. Self organizing feature maps create nonlinear projections of EMG features to obtain task-specific synergies [112, 182, 183]. Despite enhanced separation of classes, nonlinear projections are subject to overfitting the data, which increases sensitivity to transient changes in sEMG signals. Thus, they are not recommended for robust control schemes.

3.2.2. Spatial filtering. Spatial filtering is often used to decorrelate channels, similar to ICA [89–91, 184]. Though not typically used to extract synergy information, two recent studies have incorporated this concept into robust features encapsulating synergies.

Huang *et al* [123] use spatio–spectral filtering to extract common spatio–spectral pattern features. The method generates artificial channels with delayed signals and simultaneously filters in both the spatial and spectral domain to produce spectral features representing muscle synergies at particular spatial locations. The features outperformed HTD, spectral, and spatial analysis methods in offline analysis.

Ison and Artemiadis [124] use spatio–temporal filtering to extract multiresolution muscle synergy features. Each individual feature provides information at a particular temporal and spatial resolution, representing a specific muscle synergy at a given resolution. These synergies, along with the resulting feature space, are sparse, which allows a control scheme to detect meaningful synergy patterns, which were shown to be robust across subjets in a user-independent real-time control scheme. However, the method incurs the same concerns that often prevent time-frequency domain features from being implemented in control schemes.

4. Pattern recognition-based control

Pattern recognition-based control schemes use a dataset to train parameters of a decoder to transform EMG-related inputs into intended control outputs. The parameters are identified by detecting specific patterns of inputs, or pre-existing synergies, associated with the desired outputs. When using sEMG features as input, the decoder depicts individual muscle synergies relating to specific outputs. When using synergy features, the same decoder can describe complex mappings between synergies and their effect on a limb [50, 51]. The robustness of the resulting control scheme is dependent on both robust input features and a training set representative of the full set of inputs used during interaction. The choice of control scheme determines the functionality and reliability of the overall system (see figure 2).

Classification schemes are developed for training sets with discrete outputs, and have generally been studied for use with prostheses and kinematic outputs. Recent reviews on myoelectric control schemes provide detailed descriptions of the commonly used classification techniques [3, 185]. With discrete outputs, classification generally provides *sequential control*, in which only one DOF can be active at a time. However, many classification techniques have been modified to provide a form of simultaneous control. The simplist modification is to add training labels denoting simultaneous activations of multiple DOF [134, 186, 187]. Other adaptations involve slight modifications to traditional classifiers [188–191], with additional post-processing to minimize classification errors [192] and provide user-friendly *proportional controls*, in which output magnitudes are directly proportional to myoelectric input signals [55, 193] (see section 4.4.4).

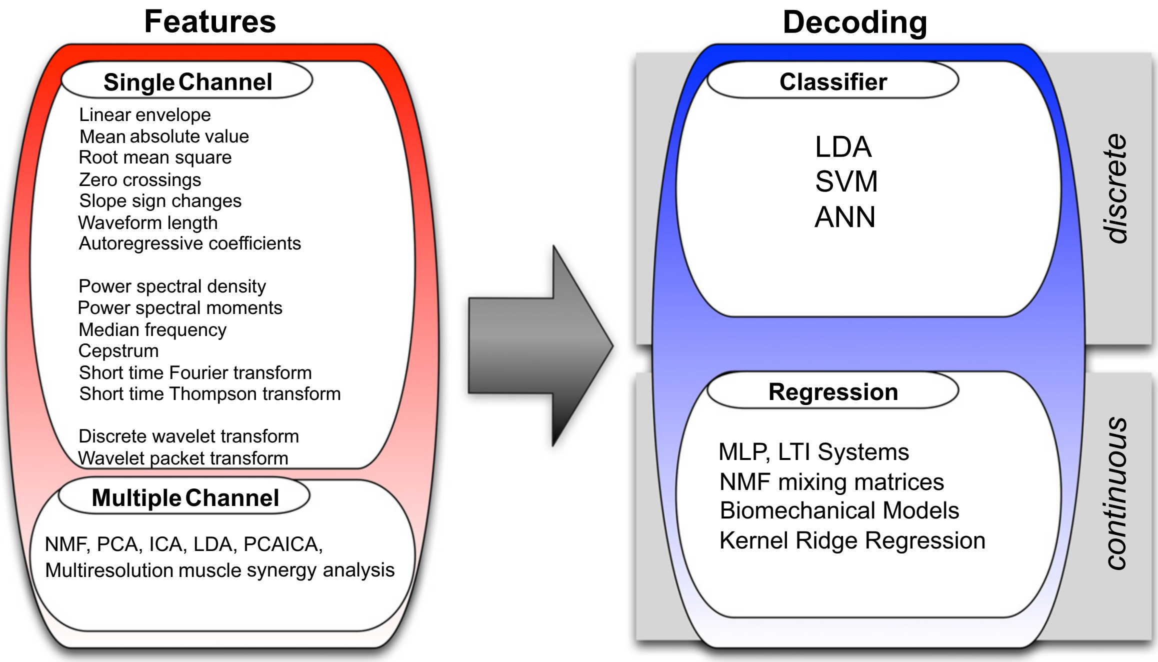

Figure 2. Choices directly effecting the robustness, functionality, and reliability of the myoelectric pattern recognition-based control scheme.

Table 3. Simultaneous control techniques via pattern recognition.

Method	Simultaneous adaptation	Advantages	Challenges
LDA	Add classes indicating combined movements [56, 134, 186], heirarchical LDA models [189], parallel classifiers for each DOF [191], conditional parallel classifiers [190]	Simple computation, effective for simple motions	Reliant on separable features, no dual association, exponential class growth with more DOF
LTI	Relate muscle synergies to motion primitives [12]	Simultaneous control of high DOF	Non-linear error fluctuations
NMF	DOF-wise calculations [44], mixing matrix [45], calibration with full output space [49], linear regression with force outputs [48]	Natural simultaneous control, simple computation	Session-independence for synergies
SVM	Parallel classifiers with electrode subsets [188], motion combinations as separate classes [187], probabilistic outputs via distance [197], regression with Gaussian kernel [14]	Optimal separation of two classes, nonlinear capabilities	No multi-class predictions, no dual association, exponential model growth with classes
ANN	Dedicated network per DOF [145], continuous outputs mimicking force [178] or kinematics [175], user choose muscle signals [15]	Dual association, continuous outputs, nonlinear separation	No global solution, multiple optimization parameters, prone to overfitting, slow training

Regression schemes are used to identify system parameters from a given training set of continuous outputs [194]. They are generally used for continuous proportional control of exoskeletons, compensating for potential user weaknesses during walking and arm movements [195]. However, the relationship between dynamic contractions and output force is not well-understood [196], and complications from cross-talk and amplitude cancellation prevent most biomechanically inspired models from applying to complex muscle interactions and multiple DOF. A more detailed explanation of the complications relating sEMG to force is provided in [59]. As a result, most regression models are designed to operate on a single DOF. However, as with classification, recent works have begun extending regression models to simultaneous control of multiple DOF. These techniques are described here, while considering the advantages and challenges summarized in table 3.

4.1. Linear controllers

Given effective feature inputs, linear controllers such as LDA [116], logistic regression [152], linear time invariant systems [12], and NMF [44], are capable of reliable simultaneous control. However, linear classifiers perform significantly worse when data is not clearly separable, as in applications with more complex motions and/or less task discrimination provided by feature extraction. Thus, synergy features are often used in linear control schemes in order to provide performance similar to nonlinear techniques without the threat of overfitting [50]. These linear models often outperform other models during real-time control [57, 198].

4.1.1. Linear discriminant analysis. Due to its computational simplicity [147], LDA is often used for real-time control. LDA extracts abstract, task-specific synergies from the set of discretized training data to predict desired tasks. It has been extended to incorporate simultaneous control suitable for using Fitts' law tests [199]. The easiest modification simply adds motion combinations to the training set as separate classes [134, 186], at the expense of less accuracy for individual motions [56]. Using this same approach, more user-friendly predictions can be obtained by training multiple binary classifiers as one-versus-one [200] and one-versus-all [201] for each class to minimize false positive predictions, avoiding unintended motion. More complex approaches train multiple LDA models in a heirarchy [189] or in parallel [190, 191] to better distinguish between DOFs, but with more computational cost. Each modification achieves simultaneous control at the expense of more complex training sets needed to create the individual models.

4.1.2. Linear time invariant models. Linear time invariant (LTI) models are used by Artemiadis *et al* to relate synergy features to anthropomorphic joint movements. The models take PCA synergy features as inputs to a model consisting of a hidden state vector, outputting a two-dimensional motion primitive subspace of four-dimensional shoulder and elbow joint movements. A maximum likelihood algorithm determines the linear relationship between muscle synergies and motion synergies, providing simultaneous control over a plane [174] and three-dimensional space [12].

4.1.3. Non-negative matrix factorization (NMF). Similar to LDA, NMF is also used directly in the control scheme to provide simultaneous control [43, 45]. Jiang *et al* [44] use a semi-unsupervised method to extract synergies specifically from each output DOF corresponding to positive and negative motion along that DOF. Then, the extracted synergies are mapped to outputs via a linear 'mixing matrix' to provide simultaneous control. Muceli *et al* [49] compare this method with applying NMF on both DOF at once, noting that full simultaneous control can be obtained using three synergies instead of four when applying separately on each DOF. Jiang *et al* [57] compare real-time performance to other classifiers with better offline statistics, noting that the intuitive controls underlying the NMF algorithm allow users to quickly adapt and achieve equal performance metrics. Berger *et al* [48] use NMF and linear regression to relate synergies with forces, verifying control via NMF as an effective strategy for motor coordination.

4.2. Nonlinear controllers

Nonlinear controllers are capable of more complex representations between sEMG and desired outputs and therefore are not as reliant on robust synergy features as linear controllers. However, there is high risk for overfitting models to training data, resulting in sensitivity to transient sEMG changes, and frequent re-training if not designed carefully [202].

4.2.1. Support vector machines. Support vector machines (SVM) guarantee a globally optimal separation of classes and achieve nonlinear classification through the use of kernel functions. However, an SVM only provides an optimal hyperplane separating two classes of data, and does not support dual association (e.g. simultaneous wrist flexion and grasping is a distinct class from grasping). For multifunctional controls, multiple SVMs need to be trained between all combinations of two classes (one-versus-one) [23], or each class versus all others (one-versus-all) [197]. The most frequently predicted class among all SVMs represents the final output.

Naik *et al* [187] effectively train seven SVMs to classify all combinations of wrist and grouped finger flexions. This works well for a small number of motions, but the number of SVMs grows exponentially with the number of classes and DOFs, and quickly becomes impractical for real-time applications. Alternatively, Boschmann *et al* [188] process two SVMs simultaneously using disjoint electrode subsets, and Bitzer *et al* [197] extend SVMs to produce probabilities based on distance to each one-versus-all SVM hyperplane for potential simultaneous control. Regression SVMs are implemented by Vogel *et al* [14], using one model per DOF for simultaneous control of a robot arm.

4.2.2. Artificial neural networks. Artificial neural networks (ANNs) include linear multi-layer perceptrons (MLP) as well as more advanced networks. In contrast to SVM, ANN is more flexible and better suited for classifying simultaneous control. Complex nonlinear mappings are produced via hidden nodes with nonlinear functions at each node. Unlike LDA and SVM, ANN supports dual association, and does not require separate classes to represent simultaneous motion. ANN outputs can also be represented as proportional and/or continuous variables rather than strictly on/off as in SVM. For example, Khokhar *et al* [131] use multi-class SVM using one-versus-one for 19 classes representing contraction levels for 2-DOF. Rather than training over 100 SVM models for proportional simultaneous control, a single ANN could simultaneously predict contraction levels for each motion.

Despite the lack of a global optimum solution, threat of overfitting to training data, slow training times, and general underperformance compared to SVMs [187], ANNs have proven to be effective for many myoelectric control schemes [24, 159, 203–207], with backpropagation networks proving robust in real-time control [202, 208].

Simultaneous control with ANN is somewhat trivial. Networks can be trained with continuous outputs representing either force [178] or kinematics [175, 209]. However, Ameri *et al* [210] indicate that training on kinematic data is slightly less robust than force data due to lower contraction levels. Jiang *et al* [145] note that a dedicated MLP for each DOF produces better results than a single network trained on all DOF. Vogel *et al* [15] allow the user to select desired control inputs while watching automated outputs. Gopura *et al* [211] use a neuro-fuzzy approach to control a 3-DOF wrist exoskeleton.

4.2.3. Other nonlinear classifiers. Other nonlinear classification techniques include random forests [212], Gaussian mixture models [152] and K-nearest neighbors [151], among others. Random forests, due to the large number of tree-type classifiers they produce, are more robust to overfitting than other nonlinear classifiers. However, processing the large number of trees in parallel makes it less appealing for real-time simultaneous control. The others are generally subject to the same curse of dimensionality and assumed Gaussian properties hindering clustering techniques in feature extraction. Many adaptations of the above classifiers have been proposed, particularly to integrate fuzzy classification, and are discussed in more detail in the related reviews [3, 185].

4.2.4. Other nonlinear regression models. Other nonlinear regression models typically only predict forces on a single DOF, using Hill-based muscle models [213, 214], other biomechanical models [215, 216], black-box approaches [217, 218], combinations of Hammerstein and Weiner models [219–222], or nonlinear polynomial models [220, 223]. Cavallaro *et al* [224] control multiple DOF on an exoskeleton using genetic algorithms and anatomical representations to optimize parameters of Hill models. Most other methods are too susceptible to overfitting to employ more than one DOF at a time. Clancy *et al* [220] evaluated parameters that prevent overfitting, and concluded that longer training sets, higher SNR, fewer modeling parameters, and system identification techniques robust to noise all contributed to less overfitting to training data. They proposed the use of multiple channels and a signal whitening processor to reduce the variability of sEMG and increase SNR, which reduced overfitting when fitting model parameters via ridge regression. Gijsberts *et al* [225] employ another approach, using incremental training to routinely update a ridge regression model with new data to limit sensitivity to transient changes.

4.3. Multimodal models

Multimodal models incorporate sensors depicting the current state of the device being controlled for more robust predictions. Kumar *et al* [226] introduce Weiner–Hammerstein components on sEMG and force sensors of an exoskeleton to predict additional forces needed for output. Vaca-Benitez *et al* [227] propose a multi-input-single-output control scheme which incorporates two sEMG channels, angular position and force exerted into an exoskeleton to output motion inversely proportional to the produced force along the intended direction of movement. Such multimodal models are likely to become more abundant because of their ability to provide more state information about the device in operation. However, the additional information indicates a greater number of parameters to estimate, so techniques for avoiding overfitting are essential for more complex control schemes which mimic fully dynamic, unconstrained motion.

4.4. Open challenges

All pattern recognition-based control schemes are dependent on a training set representing the full set of expected inputs during use. The training sets are typically intensive to acquire, requiring motions from each available task while measuring desired output. However, particular tasks only use a small subset of the entire synergy library [228], which is often not sufficient to represent complex tasks with minimal dimensionality [46]. Moreover, muscle synergies associated with a specific task are generally subject-specific, with only a sparse set of population-wide synergies providing a low-level basis for control [41]. While training strategies have been proposed to help new users create effective training sets and enhance decoder performance during actual use [229, 230], there remain major challenges associated with pattern recognition-based control schemes.

4.4.1. Session independence. Session independence is a common issue in most pattern recognition-based control schemes due to changing transient properties of sEMG and contrasts between dynamic operation and controlled training sets used to build the model. Skin impedance, muscle fatigue, atrophy and/or growth, and specifically electrode shift, posture changes, and signal intensity may all degrade the performance of a trained control scheme.

Artemiadis *et al* [11] propose a switching method to detect fatigue and switch to a model trained on similar fatigued activations. The method effectively eliminates degradation due to fatigue, but requires separate models for each fatigue level.

Hargrove *et al* [231] show the degrading effects of electrode shift on a classifier, increasing error rates by over 30% through slight shifts in electrode placement. Transversal shifts are especially impactful, as they result in measuring different motor units [85]. However, including these shifts in the original training set removes the degradation.

Similarly, posture changes can also degrade performance. In addition to biomechanical changes in muscle activations, posture changes may create slight electrode shifts with respect to underlying muscles. Scheme *et al* [232] characterized the adverse effects of changing postures on performance, and also concluded that the best way to minimize the effects is to include all possible combinations in the training set. Fougner *et al* [233] and Geng *et al* [234] propose sensor fusion as one solution, adding accelerometers and mechanomyogram signals respectively, to make classifiers more robust to posture changes, but the accuracy is still reliant on a representative dataset. Khushaba *et al* [113] recently proposed a robust spectral feature set for limb position invariance, but this has not yet been applied to real-time control.

Signal intensities also degrade performance due to changes in sEMG structure at higher contraction levels

[150], the increased presence of muscles providing co-contraction, and potential alteration of synergies at higher contraction levels. However, including all contraction levels in the training data has not minimized degradation enough to establish a usable system [25].

In a real application, it is not practical to include all combinations of tasks, fatigue levels, electrode shifts, postures, and activation levels in one training set for a fully robust control scheme. Instead, methods have been proposed using adaptive control schemes that periodically update the training set to avoid degradation. Nishikawa *et al* [208] proposed one of the first adaptation methods, allowing users to manually correct bad performance. However, the interactions required from the user are complex, and performing them multiple times can easily lead to frustration. Unsupervised adaptation techniques provide themselves with feedback based on predictions, and were proposed by Kato *et al* [235] and Chen *et al* [236]. However, these techniques are unable to correct their own mistakes, and have been shown less effective at avoiding degradation compared to supervised techniques [237]. Orabona *et al* [238] introduced a supervised adaptive model using SVM to control a prosthetic hand. The model detects the closest of a set of pre-trained SVM models based on sEMG inputs during periodic training, and adds new data to the model to update it with new information. Gijsberts *et al* [225] propose an incremental updating technique using ridge regression and random Fourier features to combat transient changes in sEMG over multiple sessions. Kiguchi and Quan [239] propose an adaptive neuro-fuzzy controller to train an exoskeleton, where force sensors on the tip of the exoskeleton are used to update the model at different postures. Pilarski *et al* [240] utilize sparse reinforcement learning provided by the user to effectively learn a control scheme that adapts to slight transient changes so long as the user maintains periodic reinforcement.

4.4.2. User-independence. Pre-trained pattern recognition control schemes have been proposed as a solution [241] to the intensive training phases that often lead to frustrations and rejection by users of myoelectric controlled interfaces [32]. However, the well-documented inter-user variability in sEMG signals has thus far prevented decoders from performing well across users. Orabona *et al* [238] partially address the issue of user-independence by utilizing pre-trained SVM models to incorporate as a basis for adaptive modeling. Adapting to a pre-trained model showed similar performance to training a model from scratch, but utilizing only a pre-trained model gave poor classification results. However, the method provides an example of using pre-trained classifiers to reduce the training burden on subjects. Castellini *et al* [241] also attempt to use pre-trained SVM models to avoid intensive training phases while classifying different grip types. They tested cross-subject performance on classifiers trained on data from other subjects and found that most subjects had a strong overlap in models, but were unable to obtain consistent classification performance, with average accuracy just above 50%.

More promising approaches have only recently been proposed. Matsubara *et al* [242] create a model of sEMG signals consisting of user-dependent features and motion-dependent features. Training their model, they are able to separate user-dependent sEMG signals from population-wide signals associated with movements. They then train a multiclass SVM on motion-dependent data. When given novel data, the method extracts the subject independent features and registers the new data to the existing model after observing one trained movement modeled in the SVM. This method has produced classification accuracies near 75% for novel users.

Khushaba *et al* [243] also recently proposed a technique for user-independent decoders. They transform robust spectral features [113] to a population-wide model, termed 'unified-style space,' using canonical correlation analysis between all features from multiple subjects. Then, a new subject only needs to perform a calibration to generate a new set of features which can be projected to the unified-style space. With this method, the authors reported accuracies above 80% in offline analysis. Moreover, it is applicable to amputees because of the robust calibration process.

Another promising approach to user-independence has been achieved by Gibson *et al* [244], requiring no calibration nor registration. They structure a simple decision tree based on biomechanical properties and expected synergies of six forearm muscle to classify five distinct hand and wrist motions. Thresholds within the decision tree are optimized via regularized nonlinear conjugate gradient descent on training data from a group of subjects. The cost function is designed to minimize misclassification error in favor of fewer motion predictions. The average accuracy presented in offline analysis was 79%, but in real-time analysis using proportional outputs similar to the ramp introduced in [133], all subjects quickly adapted to the control scheme to achieve performance rates similar to all the other subjects at greater than 90%. This adaptation is the same effect found by Jiang *et al* [57], indicating that users adapt to pattern recognition-based control schemes similar to motor learning controls.

Each of these techniques for user-independence has only been attempted on sequential controls. For simultaneous controls, mixing matrices with NMF are the closest to user-independence, as they only require an initial semi-supervised calibration while extracting synergies [49]. After the calibration, performance is very similar to motor learning-based controls, providing a degree of user-independence (see section 5).

4.4.3. Benchmark databases. Many of the pattern recognition-based control schemes presented above have reported high accuracies and correlations on data obtained specifically for the associated control scheme. Despite outstanding performance metrics in offline analysis, the large number of variables associated with the control scheme makes it difficult to compare methods against each other. Moreover, most studies only validate new methods and/or create new models with roughly ten subjects, making it difficult to prove its robustness to the general population. Benchmark databases have been established in many research fields such as machine learning [245], face recognition [246], and general object detection [247]. Recently, Atzori *et al* [248] introduced the Ninapro database, an ongoing project incorporating kinematic and sEMG data from multiple subjects, both healthy and amputees, performing 52 finger, hand and wrist movements, to provide the first form of benchmark testing for pattern recognition-based schemes. Perhaps more importantly, this database provides an opportunity to generate models based on a diverse and representative data population, potentially aiding the development of both session- and user-independent control schemes. As this database grows, and similar databases incorporate data from the upper arm and lower limb, these control schemes will have a common platform to verify the validity of new techniques on actual target users. Although this does not replace the need for real-time evaluation (see section 6.1), benchmark testing can aid the prototyping of new schemes and models for practical commercial applications.

4.4.4. Post-processing. Specific to classifier techniques, a post-processing step is often needed to interpret velocities and forces as a complement to discretized outputs. Proposed algorithms relate cumulative sEMG signal intensity to velocity/force percentages to associate with the predicted motion [249, 250]. This simple technique has proven more user-friendly than conventional on/off direct control [251]. However, it magnifies any misclassifications, making the control scheme less reliable.

Post-processing is also used to reduce the effect of misclassifications from the decoder. Given a training set representative of real-time use, one effective method is to train class transition probabilities via hidden Markov models [252]. Although Markov models have been used for both feature extraction [253] and classification [128, 254], they can also prevent unnatural transitions between outputs [132]. Amsuss *et al* [192] developed a similar scheme to correct erroneous predictions using a maximum likelihood and global mean activation patterns. Although they can assist with simultaneous control, these do not provide solutions for proportional control.

Simon *et al* [133] proposed a proportional control output method where the output is proportional to the consecutive number of classification predictions. The method successfully provides proportional controls while minimizing perceived effects of misclassification. However, limiting the proportional outputs led to frustration and unnecessarily high muscle contractions from some users who desired faster initial speeds. Scheme *et al* [255] address this through automatic normalization of outputs during training. By telling subjects to ramp their motions during the training set, the method is able to find a range of values associated with sEMG inputs for each classification output, providing a more natural proportional control at the expense of enhanced misclassifications.

5. Motor learning-based control

Motor learning-based controls use closed-loop feedback to train human motor systems to interact efficiently with a mapping function transforming sEMG-related inputs to control outputs. This method is common in brain–machine interfaces [256–258], which utilize brain plasticity to encourage users to associate thoughts with controls [259–261]. With sEMG, it is expected that humans learn to associate commands with limb motion, and many studies invoke simple control schemes to analyze the learning process as users perform a given set of tasks. Mussa-Ivaldi *et al* [262] propose that the motor system naturally learns a novel inverse map relating the effect of motor commands on task-relevant variables when interacting with myoelectric controls. This learning has been modeled and verified in the presence of closed-loop feedback [136, 263, 264], suggesting that efficient control can be achieved simply by learning to interact with the control scheme [265–267].

Most motor learning-based control schemes currently involve two-dimensional cursor control on a computer monitor in order to evaluate learning in a controlled environment. The cursor is typically controlled via position control, in which the position on the screen is proportional to activation levels of a constrained upper limb muscles in the direction of a corresponding mapping function [42, 97, 136, 264]. Variations of this control include mapping the cursor in three dimensions [51] and using velocity control with an unconstrained arm [58, 135]. The three-dimensional mapping demonstrates the potential for these schemes to achieve simulateous multifunctional control with higher DOF, velocity control expands the available task space, and unconstrained motion introduces additional complications from electrode shift and motion artifacts into the control scheme.

Ison *et al* [47] introduce a similar, but visually different control scheme involving the rotation and scaling of a virtual box on a screen to a target orientation and size. Using multiple mapping functions and having subjects interact with both velocity cursor control and box size/orientation control in random combinations, they found that learning incurred from one control interface (e.g. cursor control) transferred with little degradation to new control interfaces (e.g. box size/orientation) when using the same mapping function. This indicates that motor learning is interface independent, and can extend to many different applications. Pistohl *et al* [137] demonstrate the extension of motor learning-based schemes to the control of robots by comparing subject performance for two different myoelectrically controlled tasks. The first task is the standard cursor position control task. The second uses a similar mapping function to operate individual fingers of a robotic hand. The results show similar performance trends when given visual feedback for both cursor control and hand control, indicating that these control systems can be easily extended to applications in prostheses and other forms of robotic control.

5.1. Intuitive control

In contrast to pattern recognition-based control, mapping functions implemented in motor learning control schemes are not necessarily constrained to predict a user's intent. Chase *et al* [264] compare user performance of two unique decoding algorithms in open and closed-loop based control strategies. The control scheme involved commonly used cursor control, in which a subject is instructed to move the cursor towards a target as quickly as possible. The results show consistent significant performance differences between decoders in open loop control tasks, but convergence of performance in the online closed loop control tasks after an initial significant difference. Radhakrishnan *et al* [136] demonstrate the effect of human motor learning through interaction with two control schemes, classified as intuitive and non-intuitive, which map sEMG signal amplitude from eight upper arm muscles to two-dimensional cursor position. The intuitive decoder maps six of the eight muscles to a vector along the two-dimensional plane that is most consistent with the action on the limb when the muscle contracts. The non-intuitive decoder maps six of eight muscles randomly along equally spaced vectors in the two-dimensional plane. Subjects are able to learn the decoders in both experiments, with performance trends best fit by exponential decay. Additionally, the results show that the intuitive decoder helps subjects achieve better performance initially, but the non-intuitive decoder has a steeper learning rate that made performance for both decoders almost equal after 192 trials. Antuvan *et al* [135] perform a similar cursor control experiment with one intuitive mapping and three arbitrary mappings. Using a performance metric based on learning rates and final performance, the intuitive mapping rated worse than the other three mappings. Each of these studies conclude that intuitive decoders give better initial performance, but arbitrary decoders with worse initial performance are capable of higher learning rates and achieving similar or better performance over time when provided closed-loop feedback.

5.2. Robust control

In addition to the relaxed constraints on mapping functions, motor based control schemes appear to be naturally more robust to the degradation often seen in pattern recognition-based control schemes. Liu *et al* [266] indicate that continuous visual feedback helps subjects learn to generalize to new tasks within the same task space, indicating proper learning of the inverse model and a robust interaction. Later work from the same group [267] reveals that deciphered inverse models appear invariant to scaling changes within a mapping function during the learning process, suggesting that motor learning control may be more robust to factors such as amplitude cancellation and changes in MVC during long term use. Ison and Artemiadis [58] evaluated control performance over multiple days using cursor velocity control with non-intuitive mappings, revealing a long term learning component which improved performance efficiency. The performance was robust to any effects from electrode shifts caused by both the multiple day experiment and unconstrained motion, indicating that users not only learned the inverse mapping of the decoder, but formed a more robust identification of the entire system dynamics to prevent significant degradation even after taking a week off between experiments.

5.3. Synergistic control

Nazarpour *et al* [42] analyze motor learning in the context of muscle synergies using cursor position control tasks. They define a task space that requires simultaneous control of a pair of muscles to achieve a task, and test subjects on different combinations of biomechanically independent and antagonistic muscles. By examining user reactions to virtual perturbations in cursor position, they demonstrate the ability of humans to learn flexible control through the formation of dynamic, task-specific muscle synergies. They quantify these synergies in terms of inferred muscle correlation structure from variance in cursor position. A metric called index of covariation captures organized variance in directions bisecting individual muscle activation directions. They evaluate evolution of these synergies with a regression model using trial block number as one of the dependent variables to show that these synergies develop over time, corresponding to the increased control efficiency. Ison and Artemiadis [58] analyze synergy development during long term control of cursor velocities via two biomechanically independent pairs of antagonistic muscles. The synergy development was evaluated by analyzing changes in PCA across trials. Unlike in [42], redundant velocity control did not force specific synergy development in order to accomplish a task. Therefore, the resulting population-wide convergence to a common synergy space indicated the natural evolution of synergies while interacting with a particular mapping function. The synergies proved to be robust to potential electrode shifts and time off during the multi-day evaluation, and correlated with enhanced control efficiencies during interaction with the myoelectric interface. However, De Rugy *et al* [97] find that this dynamic formation of synergies does not occur as easily in biomechanically dependent muscles of the forearm, concluding that low-level synergy constraints may prevent fast adaptations to particular control schemes, which emphasizes the need to carefully choose muscles and their interactions required in desired mapping functions.

5.4. Open challenges

Although multiple studies have demonstrated learning efficient and robust myoelectric controls using this approach, they have yet to be validated as viable simultaneous control schemes for any myoelectric application. More work is needed to evaluate the limits to these controls as potential solutions for simultaneous multifunction control. Currently, the most complex system developed only utilizes 3-DOF [51], and it is unclear how well humans can learn more complex mapping functions incorporating a greater degree of multifunction control. More flexible control schemes may require use of muscles with biomechanical constraints, and thus more

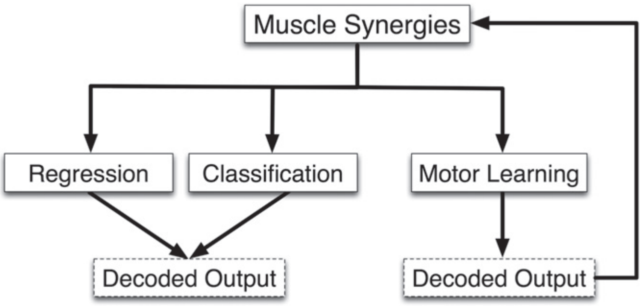

Figure 3. Myoelectric control schemes offering simultaneous control based on synergy representations. Regression and classification schemes decode outputs based on existing synergies, disregarding any adaptations due to feedback. On the other hand, motor learning schemes incorporate feedback into the development of new muscle synergies to generate robust controls.

careful planning of the mapping function would be needed to ensure the full task-space can be reached [97]. In addition, the control schemes need to expand from the traditional cursor control and demonstrate robustness in more realistic applications, such as robotic control [137]. Future research should address these issues with experiments designed to validate the control schemes for use in actual applications.

6. Future directions and considerations

Despite decades of research relating to multifunctional myoelectric control, there is a long way to go before myoelectric control schemes find their way into everyday commercial applications. Myoelectric control has historically been driven by the desire to advance prostheses, which may have stunted progress towards simultaneous multifunctional control in the past due to concerns about the functionality of residual muscles and lost muscle information from persons with amputations. However, recent advances with targeted muscle reinnervation (TMR) surgery [268], in which nerves associated with amputated muscles are redirected to residual muscle to form new functional connections, have provided an opportunity detect contractions from a full assortment of major muscles on subjects with amputations [269]. The subjects can contract the reinnervated muscles by attempting to move their missing limb, providing enhanced inputs for real time control of prostheses that were not previously possible [270]. Recently, Hargrove *et al* [271] showed that patients having undergone TMR surgery prefer the increased functionality offered by pattern recognition-based control schemes over the traditional, currently available myoelectric prostheses, despite classification error rates over 16%. Similarly, Young *et al* [56], exhibited the enhanced performance these patients can achieve when operating with simultaneous controls. In addition, Vogel *et al* [15] demonstrated that simultaneous sEMG control can even be used by people suffering from spinal muscular atrophy, even though they do not have enough strength to move their own limbs.

With the ability to extract proper muscle activity information for most potential users, the future of simultaneous multifunctional control applications relies on producing reliable control schemes utilizing robust representations of muscle synergies (see figure 3). Thus, future directions should lie in three main areas. First is the development of real time control applications and standardized metrics to compare performance across differing techniques. Second is enhanced sEMG recordings through high density surface EMG (HDsEMG). Lastly, and perhaps most importantly for commercial applications, is the development of hybrid prediction and learning schemes for user-friendly control.

6.1. Real-time control metrics

Currently, most pattern recognition-based control schemes are evaluated in offline analysis. Despite reported accuracies and correlations consistently above 90% [25], few of these methods are ever incorporated into a real-time control system. Moreover, it has been shown that offline classification accuracy and regression correlation is not representative of real-time performance [57, 145, 249]. In contrast, motor learning-based control schemes consistently report significant learning while achieving good performance metrics. However, the metrics are generally specific to the given task, and are difficult to compare to other control methods implemented in real time. Thus, in addition to an enhanced focus for real-time implementation and testing of control schemes, it is necessary to standardize metrics that can compare performance and efficiencies across different schemes, including comparisons between pattern recognition and motor learning. The Assessment for Capacity of Myoelectric Control define a set of observational performance metrics, measuring naturalness, spontaneity and compensatory motions [272]. Other works use Fitt's law tests to objectify real-time performance [134, 199, 273]. More quantitative measures are proposed in other works, defining throughput, overshoot, average speed, and direction ratio as useful indicators of real-time performance [274, 275]. Recently, Simon *et al* [276] have defined a real time target achievement control test, consisting of a set of metrics evaluating real time performance with respect to task completion and efficiency completing the tasks, exemplifying the importance to standardize a common set of metrics for useful validations.

6.2. High density surface EMG

A common solution to most of the major challenges associated with recording muscle synergies is simply recording from more electrodes on a strategically selected set of muscles. Advancements in recording technology have made HDsEMG electrodes a viable option for myoelectric controllers. The high density electrodes provide a more complete set of information to allow for richer processing and more robust control schemes. HDsEMG has traditionally been used to record from specific motor units [166]. On a macro scale, HDsEMG provides opportunities to describe two-dimensional distributions of muscle activity as well as intensity [80, 81], compensating for electrode shift and cross-talk without placing so much emphasis on exact electrode placement [277]. It also provides redundancy in signals such that they can be subset for more efficient calculations without losing control performance [49, 175]. Both Farina *et al* [278] and Assad *et al* [279] incorporate HDsEMG into a sleeve that can be worn by users, with preliminary results also showing high classification accuracies, but neither have yet to undergo extensive testing for real-time control schemes.

Yatsenko *et al* [176] used this concept to create a simultaneous multifunctional control scheme using 22 electrodes uniformly positioned around the forearm. Castellini *et al* [280] also demonstrate the potential for fine control via equally spaced electrodes around the forearm, but had concerns for overfitting that limit real-time use over longer periods of time. The use of untargeted electrodes around the forearm has become standard for pattern recognition-based wrist/hand control over recent years [56, 74, 138, 145, 147, 199, 280]. In general, placing a large number of electrodes in the same location over multiple sessions is a concern for long term use. A possible direction to combat this is the development of HDsEMG registration techniques which can automatically localize electrodes with respect to underlying muscle activity using some kind of calibration method.

In addition to the few calibration methods proposed for user-independent control (see section 4.4.2), Muceli *et al* [49] recently introduced a technique for registering muscle synergies across different electrode number, shifts, and configurations. Although this method was not designed for calibration over multiple sessions, it is a first step towards achieving one. As processing and feature extraction methods become more robust and efficient for handling large amounts of data, HDsEMG is likely to play a larger role in future control schemes, and automatic sEMG registration will be in high demand.

6.3. Hybrid prediction and learning

One of the major limitations for current myoelectric controls is the intense training and/or learning phase required by the user. Attempts to reduce the training phases have been made in classification schemes using adaptive learning and pre-trained models [237, 238, 241–243]. Even with full training phases on a single user, pattern recognition-based schemes commonly require an initial adaptation to the outputs when controlling the device in real time [12, 14, 133]. Jiang *et al* [57] show how these adaptations equalize performance of control schemes during real-time use despite having large variations in offline performance. However, not enough research has been done to evaluate user response to these additional small learning phases nor the large learning phase required in motor learning control schemes. Gibson *et al* [244] demonstrated that a control scheme trained on a variety of users can extract low-level population-wide synergies and provide good performance in offline analysis, and better performance in real-time given visual feedback. Additionally, recent implementations of simple control schemes based on extracted synergies have shown robust performance compared to more complex classifiers [43–45]. These results suggest that intuitive, user-independent control schemes can be developed to provide user-friendly, low-level control without requiring an intense training phase from the user. Such a low-level control scheme could be combined with a high-level motor learning-based scheme that a user could slowly learn over time to achieve more efficient, precise control of the device. This hybrid approach, composed of both utilizing natural population-wide synergies and developing new population-wide synergies, may be the key to efficient, user-friendly simultaneous multifunctional control that is widely accepted by users.

7. Conclusion

Robust simultaneous multifunctional myoelectric control is a necessary achievement for commercial applications in prostheses, orthoses, and robotic control. Muscle synergies play a crucial role in these control schemes due to the inherent necessity to extract temporal activation patterns between multiple muscles. To date, these controls have struggled in real-time control due to the high variability of sEMG signals. When designing a new control scheme, the selection of muscles and placement of sEMG electrodes is an essential component determining the potential success of the scheme. Synergy features can produce robust activation signals used for input to a linear decoder to output complex but intuitive control variables. The decoder can be designed using pattern recognition or motor learning-based control schemes depending on the desired control outputs and interactions from the user. Motor learning schemes have so far proven more robust to degradation, but require a potentially non-intuitive learning phase. Pattern recognition schemes generally require a training phase that must be updated periodically to avoid degradation. Future directions for achieving more robust myoelectric control for multiple DOF include high density electrode processing, potential hybrid approaches utilizing low-level intuitive controls with high-level controls that must be learned for precision control of a device, and reporting of real time performance metrics to account for usability. Although a lot of advances are needed for robust commercial applications, myoelectric controls remain a technique with potential to significantly change human–robot interaction.

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