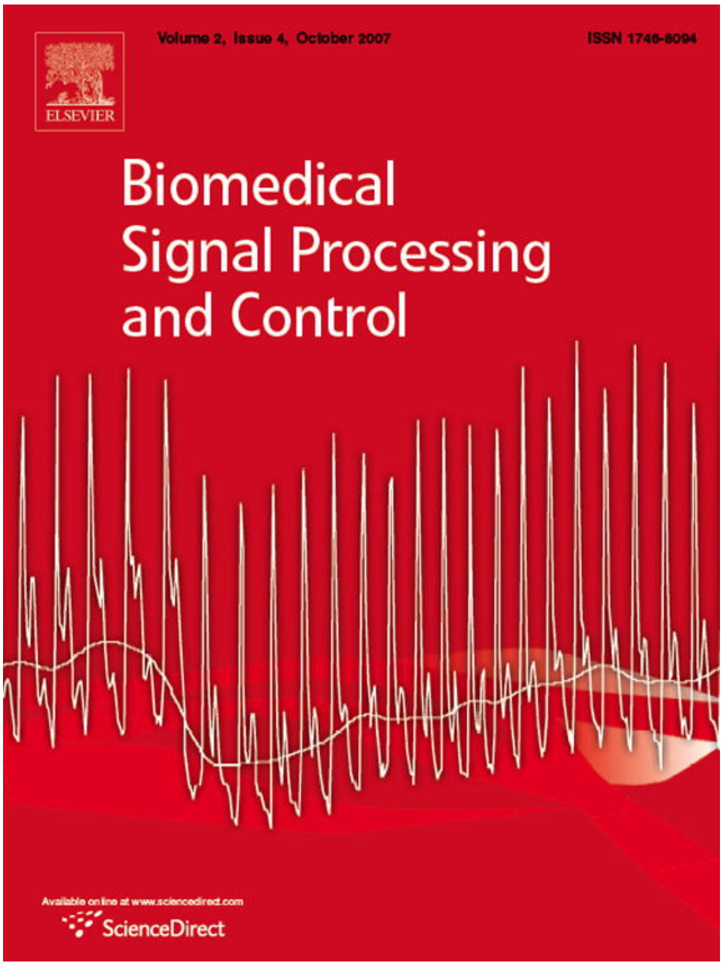
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Review

Myoelectric control systems—A survey

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Abstract

The development of an advanced human–machine interface has always been an interesting research topic in the field of rehabilitation, in which biomedical signals, such as myoelectric signals, have a key role to play. Myoelectric control is an advanced technique concerned with the detection, processing, classification, and application of myoelectric signals to control human-assisting robots or rehabilitation devices. This paper reviews recent research and development in pattern recognition- and non-pattern recognition-based myoelectric control, and presents state-of-the-art achievements in terms of their type, structure, and potential application. Directions for future research are also briefly outlined.

Keywords: Myoelectric control; EMG-based control; Myoelectric signals; Feature extraction; Classification; Pattern recognition

Contents

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1. Introduction

As many disabled people have difficulty accessing current assistive robotic systems and rehabilitation devices, which have a traditional user interface (such as joysticks and keyboards), more advanced hands-free human–machine interfaces are necessary. Myoelectric signals (MES) contain rich information from which a user's intention in the form of a muscular contraction can be detected, using surface electrodes. It is clear that amputees or disabled people are able to generate repeatable, but gradually varying, myoelectric signal patterns during different levels of static muscle contraction or dynamic limb motion. These patterns can be used in a control system, known as a myoelectric control system (MCS), to control rehabilitation devices or assistive robots.

The most important advantage of myoelectric control over other types of control system, such as body-powered mechanical systems, is its hands-free control; according to a user's intention. MES is non-invasively detected from the surface of skin, and can be adapted for proportional force or speed control in a control scheme. In myoelectric control, the muscle activity, which is required to provide a control signal, is relatively small and can resemble the effort required from an intact limb. Myoelectric control is now a competent alternative for mechanical body-powered systems in commercial functional prosthesis. It provides more proximal functions and cosmetic appearance. Moreover, wide spread potential applications for myoelectric control have been reported; including multifunction prosthesis [1,2], wheelchairs [29,33,34], gait generation [7,14], grasping control [15,25,35], virtual keyboards, gesture-based interfaces [28], virtual worlds [26], and diagnoses and clinical applications, such as functional neuromuscular stimulation (FNS) [12,16], and detection of preterm births based on uterine myoelectric signals [23]. However, despite many advances, capabilities and potentials, myoelectric control has a significant distance from professional and commercial applications. It needs complementary interfaces to deal with all requirements for fine control and suffers a lack of sensory feedback in comparison to traditional control methods.

Since the 1960s when the first clinically viable myoelectric prosthesis was presented by Russian experts, myoelectric control has not seen any revolutionary development, rather incremental evolution. Important achievements in the last 40 years have mainly been pioneered by universities in North America, such as North-Western University, Temple University, Chalmers University, the University of California, the University of New-Brunswick, and Massachusetts Institute of Technology; as well as some Japanese and Italian universities [45]. Achievements in myoelectric control can be summarized in three distinct generations. The first generation often offers ON/OFF control schemes with a single speed or single rate of actuation. The second generation includes a state machine, large-scale threshold manipulation, signal amplification, the adjustment of muscle contraction rate, and proportional control. The third generation incorporates programmable microprocessors that allow an infinite range of adjustment of myoelectric characteristics.

Application of a microprocessor in myoelectric control (which is growing notably) benefits both functionality and cost. It provides the ability to employ advanced signal processing methods, and artificial intelligence (AI), as part of a control system; as well as adapting easily, control options, and adjusting input characteristics. It also allows more complex filtering of signals, which results in increased responsiveness. Most importantly, it accommodates pattern recognition-based control schemes, which increase the variety of control functions, and improve robustness. Myoelectric control systems can be divided into two groups: pattern recognition- and non-pattern recognition-based [32]. In the former group, the desired classes of functions are discriminated from signal patterns by classifiers, and the variety of functions depends directly on classification performance. In contrast, non-pattern recognition-based controllers, which are mainly constructed on threshold control and/or finite state machines, merely output limited and pre-defined control commands based on a sequence of input signal patterns.

This paper reviews part of the numerous literatures that has been published in the last 15 years, to clarify the state-of-the-art in myoelectric control. It describes and categorizes the structure of myoelectric control systems, and demonstrates various approaches and methods applied to its components. It also counts some potential applications that have been employed in research works. The remainder of this paper is organized as follows: the structure of pattern recognition-based myoelectric control system is introduced in Section 2. Its components, namely data segmentation, feature extraction, and classification modules, are presented and analyzed in Sections 3–5. Online training of a classifier is discussed as a subsection in Section 5. Non-pattern recognition-based controllers are briefly discussed in Section 6. Section 7 introduces potential applications and open problems. Finally, conclusion, and future directions are presented in Section 8.

2. Pattern recognition-based myoelectric control

Fig. 1 depicts the main components of typical pattern recognition-based myoelectric control. Surface myoelectric signals (MES) are collected by electrodes placed on the skin over a user's muscle. Electrodes are often accompanied by miniature pre-amplifiers to differentiate small signals of interest. Signals are then amplified, filtered, digitized via standard EMG instruments, and finally transferred to a controller, which includes four main modules:

- *Data segmentation*: Comprises various techniques and methods that are used to handle data before feature extraction to improve accuracy and response time.
- *Feature extraction*: This module computes and presents pre-selected features for a classifier. Features, instead of raw signals, are fed into a classifier to improve classification efficiency. Selection or extraction of highly effective features is one of the most critical stages in myoelectric control design.
- *Classification*: A classification module recognizes signal patterns, and classifies them into pre-defined categories. Due

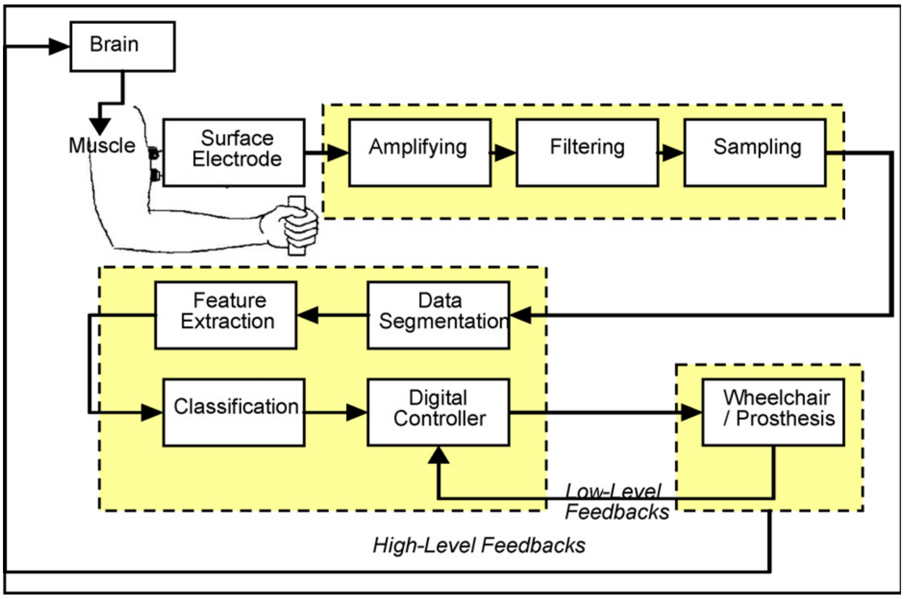

Fig. 1. A myoelectric control system based on pattern recognition.

to the complexity of biological signals, and the influence of physiological and physical conditions, the classifier should be adequately robust and intelligent. It should be able to adapt itself to changes during long-term operation, by exploiting offline and/or online training.

- *Controller*: Generates output commands based on signal patterns and control schemes. Post-processing methods, such as majority voting, which are often applied after classification to eliminate destructive jumps and make a smooth output, are included in this module too. Although some closed loop control schemes, such as obstacle avoidance, can be implemented using sensory feedback, myoelectric control structurally suffers from a lack of feedback. High-level feedback, such as visual or sensation information, can improve the quality of control and dexterity. Due to limits in applying feedback to a neuromuscular system, data fusion applied in MES, and complementary sensory feedback, can improve control performance. Each mentioned module has an important and inevitable function. However, in some cases modules may be omitted or merged together. For example in Ref. [16], a time-delayed artificial neural network (TDANN) was fed directly by raw signals. Hence, data segmentation and feature extraction modules were merged into a complex classifier.

Myoelectric control should provide a high degree of intuitive and dexterous control, and offer a high level of performance. Three important aspects of controllability in myoelectric control are: (i) the accuracy of movement selection, (ii) the intuitiveness of actuating control, and (iii) system response time [2]. System accuracy is essential to a realistic realization of user intention. It must be as high as possible, though it is difficult to define a threshold of acceptability, as no definitive clinical attempts have addressed this issue. With reference to the "hot coffee problem", the slipping of a cup of hot coffee in a prosthetic hand is not acceptable, even though the holding of a cup succeeds in 99.9% of laboratory tests. Accuracy is a key factor in developing a multifunction controller, and can be improved by extracting more information from muscle states, and adopting a powerful classifier that is capable of exploiting this information. Furthermore, increasing the number of active muscles that are used in data collection, and developing a feature set with rich information, leads to a boost in system accuracy.

The lack of intuitiveness originates in a gap between a user's current and required knowledge to perform an action. It is achievable by increasing user's knowledge, or by reducing the required knowledge to perform an action. The former needs extensive training, while the later necessitates the development of powerful and intelligent user interfaces. Therefore, myoelectric control should be capable of learning muscle activation patterns that are used in a natural way to actuate motions. They need to be adequately robust against varying conditions during operation, and highly efficient in confronting novel data or patterns. Intuitiveness relieves the mental burden on a user during long-term operation and natural daily work.

The response time of a control system should not create a delay that is perceivable by a user during operation. Having smooth and continuous control imposes real-time constraints on myoelectric control systems. There is a trade-off between response time and accuracy; this will be discussed in detail in the next section.

3. Data segmentation

A segment is a time slot for acquiring myoelectric data considered for feature extraction. Due to real-time constraints, an adjacent segment length plus the processing time of generating classified control commands should be equal or less than 300 ms. Furthermore, a segment length should be

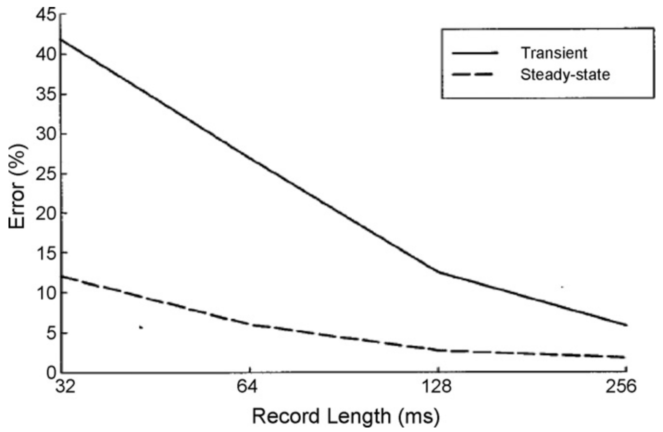

Fig. 2. Classification error compared to segment length [1].

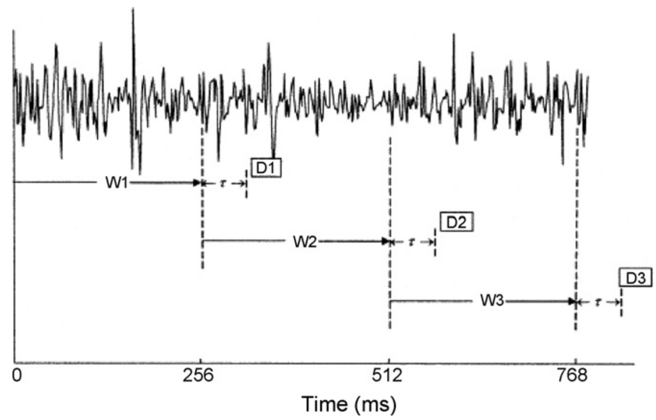

Fig. 3. Adjacent windowing techniques [2].

adequately large, since the bias and variance of features rise as segment length decreases, and consequently degrade classification performance. Therefore, as depicted in Fig. 2, a trade-off in response time and accuracy exists. However, Englehart and Hudgins [2] highlighted that by adopting continuous segmentation on a steady state signal, segment length can be reduced to 128 ms, or even 32 ms, without a considerable decrease in accuracy. Because of real time computing and high-speed microprocessors, processing time is often less than 50 ms, and segment length can vary between 32 and 250 ms.

A myoelectric signal comprises two states: (i) a transient state emanating from a burst of fibers, as a muscle goes from rest to a voluntary contraction level and (ii) a steady state emanating during a constantly maintained contraction in a muscle. Hudgins et al. [31] were the first to consider the information content of a transient signal that comes with the onset of a contraction. Although features extracted from a transient state, roughly 100 ms after onset, show a high capability for classification, it is not clear whether this is because of electrophysiological determinism or other reasons, such as skin stretch potentials or electrode motion. The main weakness in using a transient state in myoelectric control is that contractions should be initiated from rest. This prohibits switching from class to class in an effective or intuitive manner, and impedes the coordination of complex tasks involving multiple degrees of freedom. Therefore, it is attractive to consider the application of a steady-state signal in real-time control.

Englehart et al. [1] showed that steady-state data is classified more accurately than transient data, and classification suffers less degradation with shorter segment lengths (Fig. 2). The rate of classification degrades more quickly as the segment length of transient data is decreased, than with steady-state data. Therefore, steady-state data with a shorter segment length, such as 128 ms, is more reliable if a faster system response is required. A myoelectric signal has an undetermined state during transition between different levels of contractions; therefore, most errors in classification occur when switching between classes. In addition, due to the intrinsic inertia of devices, robots would not be able to respond to transitory states. As a result, the detection and elimination of data segments belonging to a transition period, can improve accuracy in a controller. This can be most applicable when generating a reliable training data set. Huang et al. [3] omitted three segments of training data during each motion changeover; in order to improve the quality of training data.

After segment length and the state of data, a third important point in data segmentation is the data windowing technique. There are two major techniques in data windowing: adjacent windowing and overlapped windowing. In adjacent windowing, as shown in Fig. 3, adjacent disjoint segments with a predefined length are used for feature extraction; and a classified intended motion emerges after a certain processing delay. Since processing time is a small portion of segment length, the processor is idle during the remaining time of the segment length. The second technique uses the mentioned idle time of the processor to generate more classified outputs. In this technique, as shown in Fig. 4, the new segment slides over the current segment, with an increment time less than the segment length. This should be greater than the processing time, because the processor must compute the feature set and generate a decision, before the next segment arrives. Englehart and Hudgins [2] investigated the effect of a segment increment on classification performance. A smaller segment increment produces a more dense but semi-redundant stream of class

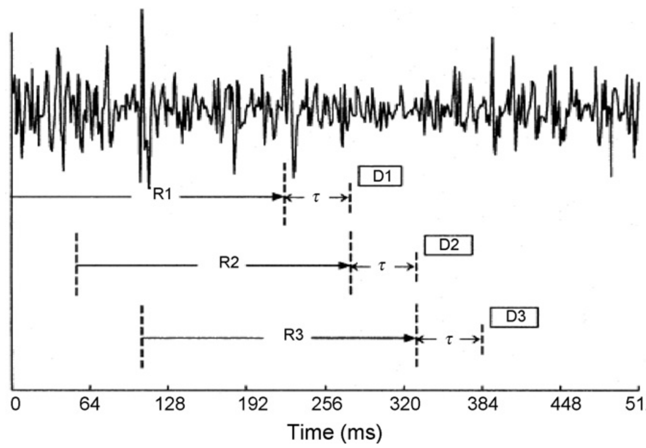

Fig. 4. Overlapped windowing techniques [2].

decisions that could improve response time and accuracy [2]. Farina and Merletti [36] showed that overlapped segments merely increase processing time, without providing a significant improvement in the accuracy of spectral features, such as autoregressive coefficients. They also showed that a segment length less than 125 ms, leads to high variance and bias in frequency domain features.

3.1. Continuous segmentation

Continuous segmentation or continuous classification, was presented by Englehart and Hudgins [2]. It performs full utilization of the computing capacity of a processing system, and produces classification results very fast. In continuous segmentation, a dense stream of decisions is produced using overlapped segments. Continuous segmentation relies on both transient and steady-state myoelectric data. Post-processing methods are designed to manage excessive classified output, and improve system performance.

Majority voting (MV) is post-processing that was applied in Ref. [2] after classification, to make a smooth and reliable decision from a dense stream of class decisions. It includes the last and next m-decisions for a given point, to generate a new decision. The final decision of each point is merged based on the greatest number of occurrences in $2m + 1$ decision points. The number of decisions used in MV is determined by processing time and acceptable delay. Acceptable delay for a system is the duration between signal onset for an activity, and the first generated decision. It would be equal to the processing time, if no post-processing was done, and would be equal to or more than the processing time of an m-decision, if MV were performed. The delay to compute the next m-decision for MV should be less than the acceptable delay time of the system. As mentioned, the accuracy of myoelectric control degrades rapidly when decreasing segment length. Englehart and Hudgins [2] point out that this degradation would be prevented if majority voting were applied as post-processing after classification. This is justified by the fact that further decisions are available with shorter segments. Fig. 5, in which T_a and T_d represent segment length and acceptable delay, respectively, indicate that classification rate remains approximately constant when decreasing segment length (T_a).

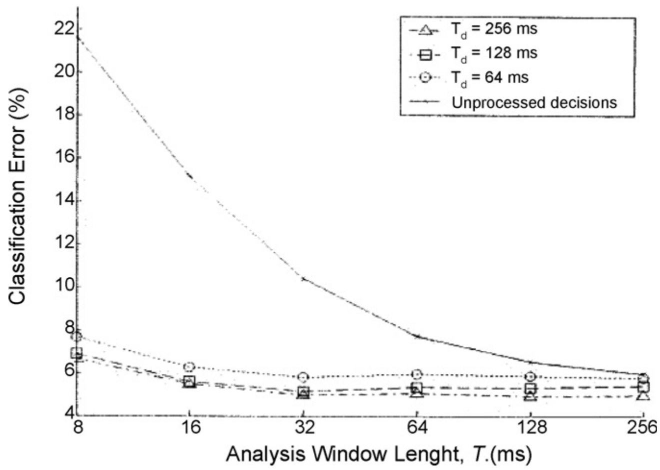

Fig. 5. Classification error vs. segment length with/without MV [2].

Performance improves when a longer acceptable delay is prescribed, as this allows more decisions in MV processing at the expense of response time. Perhaps surprisingly, the best performance is achieved when a segment length of 32 ms [2] is employed. The implication is that with a very short analysis, segment accuracy is not compromised, and very little storage space is needed for necessary computations. This is very important with regard to the implementation of a classifier as an embedded system, where memory is usually a scarce resource. Moreover, at 32 ms, system accuracy does not degrade substantially; as acceptable delay is reduced from 256 to 128 ms, allowing a system to be much more responsive.

4. Feature selection

Feeding a myoelectric signal presented as a time sequence, directly to a classifier, is impractical, due to the large number of inputs and randomness of the signal. Therefore, the sequence must be mapped into a smaller dimension vector, which is called a feature vector. Features represent raw myoelectric signals for classification, so the success of any pattern recognition problem depends almost entirely on the selection and extraction of features. A wide spectrum of features has been introduced in literature for myoelectric classification. Features fall into one of three categories: time domain, frequency (spectral) domain, and time-scale (time–frequency) domain [44].

There are two approaches to feature evaluation: structural and phenomenological approaches. In the former, features are evaluated based on physical and physiological models, considered in a signal generating process. In this approach, selected features can be evaluated using synthetic signals generated by mathematical models. Some characteristics of features, such as bias, variance, and the level of sensitivity to noise, can be measured in this approach. The phenomenological approach roughly interprets stochastic signal notwithstanding its generating structure. In this approach, which is occasionally called the empirical approach, features are mainly evaluated based on a rate of classification performance, and their robustness.

4.1. Structural analysis

A myoelectric signal is formed by the superimposition of individual action potentials (AP), generated by irregular discharges of active motor units (MU) in a muscle. Merlo et al. [24] modelled a surface myoelectric signal as

$$s(t) = \sum_j \mathrm{MUAP}\,T_j(t) + n(t) = \sum_j \sum_i k_j f\left(\frac{t-\theta_{ij}}{\alpha_j}\right) + n(t)$$

where k_j is an amplitude factor for the jth motor unit, $f(\cdot)$ the shape of the action potential discharge, θ_{ij} the occurrence time of MUAP, α_j a scaling factor, and finally $n(t)$ is the additive noise.

Due to a high number of overlapped motor unit action potentials (MUAP), and the irregular nature of MU discharge, a surface signal might be considered a complex and non-stationary stochastic signal. Characteristics of the signal are extremely dependent on the level and duration of contraction, dynamic or static muscle states, fatigue, and sweat from skin. Surface myoelectric signals, particularly at higher contraction levels, have frequently been assumed Gaussian processes with a zero-mean value. Some studies have found that the distribution is more sharply peaked near zero than Gaussian. Certainly, at low levels of contraction, or near muscle fatigue, a signal is more likely to be a Laplacian process with a zero-mean value [42]. Bonato et al. [41] used a truncated Gaussian for signal synthesis. Farina and Merletti [36] considered Shwedyk's model, and simulated a signal by filtering with Gaussian noise. They made the simulated signal non-stationary by varying generating parameters over time.

Data features computed over a time segment are inherently an approximation of the true value of a feature, with an associated bias and variance. They depend intensively on the segment length, as discussed in Section 3, and the method of feature extraction. Amplitude and power spectrums are two main characteristics of a signal that are mostly employed in feature extraction. Amplitude and its related features are often investigated in time domain analysis, while a power spectrum is usually studied in a frequency domain analysis. Using wavelet tools, powerful signal features are extracted in a time-scale domain. Fig. 6 illustrates the key parameters in each domain of signal analysis.

4.1.1. Time domain features

Because of their comparative computational simplicity, time domain features are the most popular in myoelectric classification, and are based on signal amplitude. Considering myoelectric as a zero-mean stochastic signal, amplitude can be defined as the time-varying standard deviation (STD) of a signal, which is proportional to the number of active motor units and rate of their activation. Amplitude, which is represented by the features, indicates signal energy, activation level, duration, and force. It is influenced by factors such as electrode location, the thickness of tissues, the distribution of motor units in muscle fiber, muscle conduction velocities, and the detection system used to acquire the signal. To judge the quality of amplitude features, the signal-to-noise ratio (SNR) is defined as the mean value of samples in a segment divided by their standard deviation. This ratio is a measure of random fluctuation in signal amplitude, and higher SNR yields better features. When force or posture is changing, this is no longer a useful measure.

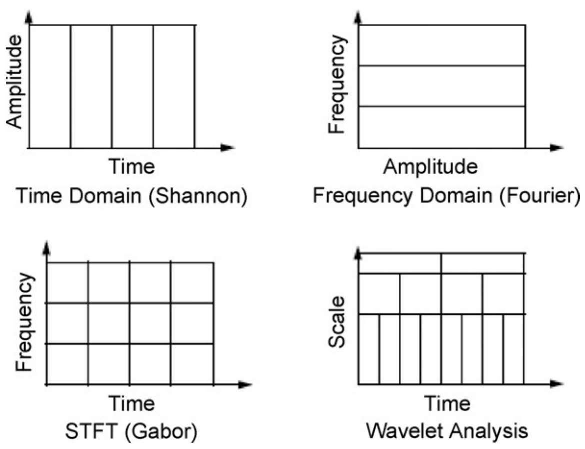

Fig. 6. Different domains of signal analysis [43].

Mean absolute value (MAV) and root mean square (RMS) are two well-known time domain features that are compared in Ref. [42]. Theoretically, when a signal is modelled as a Gaussian random process, RMS provides the maximum likelihood estimation of amplitude in a constant force and non-fatiguing contraction. In this model, SNR $\cong \sqrt{2N}$, where N is the number of statistical degrees of freedom. MAV provides a maximum likelihood estimate of the amplitude, when a signal is modelled as a Laplacian random process. In this case SNR $\cong \sqrt{N}$, which is 32% lower than a Gaussian-based model. A Gaussian model and consequently RMS, fit better at a high level of contraction; while a Laplacian model and MAV fit well for low contractions and fatigued muscles. Clancy et al. [42], experimentally found that a myoelectric signal model for a constant-force, constant-posture, non-fatiguing contraction, falls between Gaussian and Laplacian models; and on average the Gaussian model fits better. They concluded that amplitude estimated via MAV, may be at least as justified as RMS (both from a theoretical and experimental perspective), and there is little reason to argue between them.

Clancy et al. [42] also pointed out that signal whitening and the application of multi-channel signals, reduce the variance in amplitude features without increasing bias; while smoothing reduces variance at the expense of increased bias. Farina and Merletti [36] also performed a structure-based comparative review of MAV and RMS. They established that pre-whitening improves considerably amplitude features (by decreasing their variance), though it causes a problem when recording a calibration signal. They recommended an Autoregressive filter, with an order of 3–5 for signal pre-whitening.

4.1.2. Frequency domain features

Spectral (frequency domain) analysis is mostly used to study muscle fatigue, and infer changes in MU recruitment. A signal spectrum is influenced by two factors: the firing rate of a recruited MU in the low-frequency range (below 40 Hz), and the morphology of the action potential travelling along a muscle fiber in a high-frequency range (above 40 Hz) [21]. It is time variant, and directly depends on the contraction force, muscle fatigue, and inter-electrode distance. During a constant voluntary contraction, even when there is no voluntary change of muscle state, a myoelectric signal should be considered a non-stationary signal; due to the inherent physiology of an organ. However, it was shown in Refs. [22,37], that during relatively low-level (20–30% MVC), and short-time contractions (20–40 s), it can be assumed to be wide-sense stationary.

Moreover, at higher levels, 50–80% of MVC, it can only be assumed locally stationary for a period of 500–1500 ms. Therefore, a myoelectric signal can be assumed stationary in real-time applications, even if it has variant spectral characteristics.

Power spectral density (PSD) plays a major role in spectral analysis. In wide-sense stationary stochastic signals, PSD is defined as a Furrier transform of the autocorrelation function of a signal. Its two characteristic variables, the mean and median frequency (f_{mn}, f_{md}), provide some basic information about signal spectrum and its change over time. Spectral analysis based on a Fourier transform is widely developed using either periodogram or parametric methods. In periodogram, PSD is estimated using the square of a Fourier transform of a signal, divided by signal length. This method has four problems, namely (i) frequency leakage related to pre-windowing, (ii) frequency resolution related to short-time segments (to preserve a stationary signal), (iii) large estimation variance, and (iv) an assumption of signal periodicity or signal zero equal to outside an analysis interval.

In a parametric method, an autoregressive (AR) model is used for PSD estimation. This may avoid the problems listed above, but the main problem is the determination of its order. There are several algorithms to determine this: including Akaike information criterion (AIC), and the minimum description length (MDL). However, neither of these work very well for non-AR data. Moreover, they tend to model some noise, especially certain motion artifacts, rather than a signal.

Farina and Merletti [36] presented a comparative review of mean and median frequency estimation, using periodogram and parametric methods in stationary and non-stationary conditions. They showed that the order of AR models in spectral estimation is not critical, and a model with an order of 10 works appropriately for any segment length (Fig. 7). To reduce the computational cost, AR models with an order 6, are the optimal choice in real-time applications with a segment length of 250 ms. An AR model outperforms the periodogram method in a short segment length; both under stationary and non-stationary conditions. They point out that a segment length of 250–500 ms for non-stationary conditions is suitable for achieving less variance and bias in estimation, but lengths shorter than 125 ms are to be avoided, because they lead to high variance and bias. Segment overlapping is not recommended, as it increases computation without providing significant improvements in the quality of feature estimation.

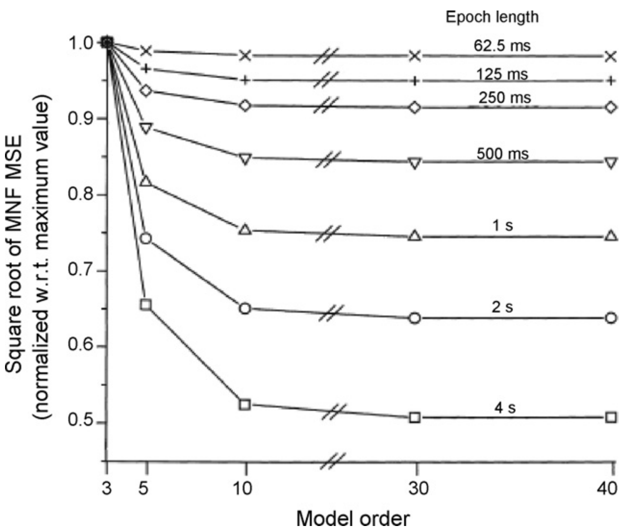

Fig. 7. Changes in PSD features vs. AR model order [36].

4.1.3. Time-scale features

In spectral analysis, a Fourier transform (FT) loses signal time domain information, and cannot tell when a particular event took place. This is acceptable for stationary signals, as their properties do not change over time. However, myoelectric signals contain numerous non-stationary or transitory characteristics. A short-time Fourier transform (STFT), maps a signal into a two-dimensional function of time and frequency; but it merely obtains this information with limited precision determined by the size of the analysis window. A wavelet transform (WT) enables local analysis to be performed, i.e. to analyze a localized area of a larger signal. Wavelet analysis reveals data aspects that other techniques miss, such as trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Furthermore, wavelet analysis can often compress or de-noise a signal, without appreciable degradation. Fig. 6 illustrates different domains in signal analysis.

There is a correspondence between scale and frequency in wavelet analysis: a low scale shows the rapidly changing details of a signal with a high frequency and a high scale illustrates slowly changing coarse features, with a low frequency. Therefore, WT acts as a ‘‘mathematical microscope’’, in which one can monitor different parts of a signal by just adjusting focus. As a generalization of WT, a wavelet packet transform (WPT) allows the ‘‘best’’ adapted analysis of a signal in a time-scale domain. The fundamental difference between STFT, WT, and WPT is the way they partition the time-scale axis. STFT has a fixed partitioning ratio; each cell has an identical aspect ratio in time and frequency. The partitioning ratio of WT is variable; the aspect ratio of cells varies such that frequency resolution is proportional to centre frequency. This partitioning has been shown to be more appropriate for many physical signals, but the partition is nevertheless still fixed. WPT provides adaptive partitioning; a complete set of partitions are provided as alternatives, and the best for a given application is selected. Fig. 8 shows three partitioning methods used in STFT, WT, and WPT. Besides feature extraction, time-scale analysis can be used for signal de-noising, identifying fatigue in long-term

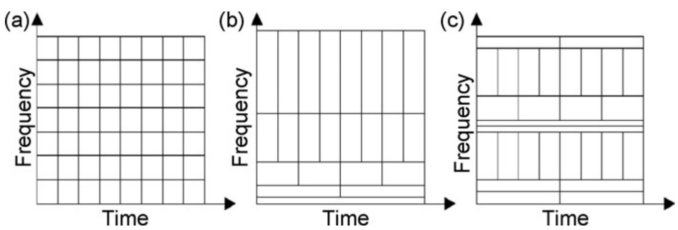

Fig. 8. Three partitioning methods used in Ref. [27]: (a) STFT, (b) WT, and (c) WPT.

activity, and isolating coordinated muscle activities. Reconstructed de-noised [38] myoelectric signals can show muscle activity more clearly.

Karlsson et al. [21,22] presented two independent investigations in using WT and WPT for myoelectric signal analysis during static and dynamic contractions. It was shown that a wavelet shrinkage method is a very useful tool in signal analysis during static contractions, because of its de-noising characteristics. Wavelet shrinkage in WPT and FFT significantly reduced the mean square error of spectral estimates. In dynamic contraction, the non-stationary properties of a signal become dominant. This is because of a change in the number of active motor units, the spatial distance between electrodes, and the innervated zone and changes in fiber length. Karlsson et al. [22] compared the accuracy and reliability of the continuous wavelet transform (CWT) method with other time-frequency methods during dynamic contraction. The results suggest that CWT shows better statistical performance than any other time-scale analysis method used in their study on simulated signals. It was concluded that CWT is a useful tool for the analysis of MES, in spite of its computational inefficiency.

4.2. *Phenomenological analysis*

The common theme in all phenomenological methods is that they provide a feature set that improves signal classification performance. This can mainly be achieved in two ways: feature subset selection and feature projection. The former approach searches all existing features in a feasible feature space in order to choose an optimal subset that result in the highest classification rate. The later approach creates a subset of new features via a combination of existing features based on a linear or nonlinear mapping.

Feature subset selection requires a search strategy that selects a candidate subset, and an objective function that evaluates these candidates. There are many search strategies for feature subset selection, such as sequential forward selection, sequential backward selection, and sequential floating selection; as well as random search strategies such as branch and bound, simulated annealing, and Genetic algorithms. An objective function can be either a geometric separability measure, or the hit rate of a classifier. The authors [46] presented feature subset selection, to find an optimal subset of myoelectric features using cascaded genetic algorithms as a search strategy, and a Davies–Bouldin index as a class separability measure.

Feature projection is mostly applied to cope with the curse of dimensionality that occurs when using time-scale features. A wavelet transform generates many coefficients to represent time-scale features. These need to be mapped into a lower dimension, while preserving the most discriminative information. Principal component analysis (PCA) and linear discriminant analysis (LDA) are the two main linear mapping functions that are used for feature projection. The former is based on signal representation criterion, and the later on classification criterion. Englehart et al. [1,27], presented a comparative investigation into applying linear projection in time-scale features; and Chu et al. [5] proposed a linear–nonlinear projection method composed of PCA and a self-organized feature map (SOFM). These are both discussed in the next section.

4.2.1. *Time-domain and time-scale features*

Hudgins et al. [31] applied five time-domain features of transient myoelectric signals for classification. The features were the mean absolute value (MAV), mean absolute value slope (MAVS), zero crossing (ZC), slope sign changes (SSC), and waveform length (WL). They are based on signal amplitude, though the resultant values give a measure of signal amplitude, frequency, and duration. This set gained a rate of 91% accuracy via MLP neural networks.

Englehart et al. [27,1] applied feature projection to compare the final performance of classification. They compared the performance of time-domain features used in Ref. [31], with time-scale features comprised of a short-time Fourier transform (STFT), wavelet transform (WT), and a wavelet packet transform (WPT). STFT with a window length of 64 points and overlap of 50%, WT with a fourth order of Coiflet wavelet, and WPT using a Symmlet wavelet of order five, were adopted as signal features. A modification was applied on time-scale partitioning for WPT, to maximize the ability of discrimination. It was based on using the level of class separation as the cost function. To avoid overloading the classifier, features were reduced in the dimension, using principal components analysis (PCA). The classification-hit rate was not sensitive to the dimension; but to decrease the burden of the classifier, and achieve a required response time it was critical to success. It was shown that PCA is superior to other methods of dimension reduction. The results indicated that classification performance improved in a progression from TD, STFT, WT to WPT, indicating the relative efficacy of the feature sets. The wavelet and wavelet packet-based feature sets, as depicted in Fig. 9, outperformed the other features. The best performance was obtained by WPT features, PCA reduction, and LDA classification; yielding an average error of 0.5% for four-class, and 2% for six-class classification problems [1]. This was a significant improvement over Hudgins et al. [31].

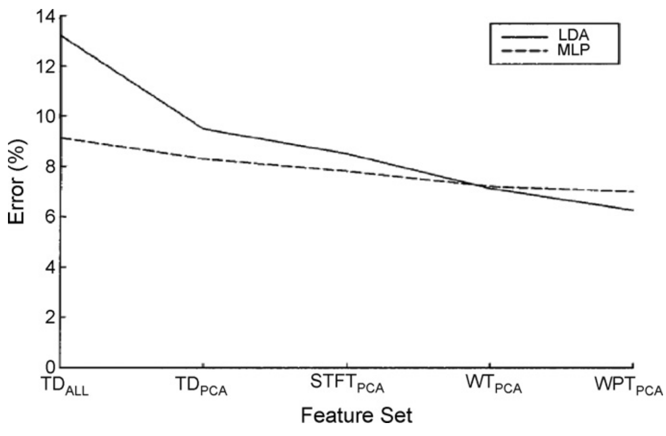

Fig. 9. Classification error for different features [1].

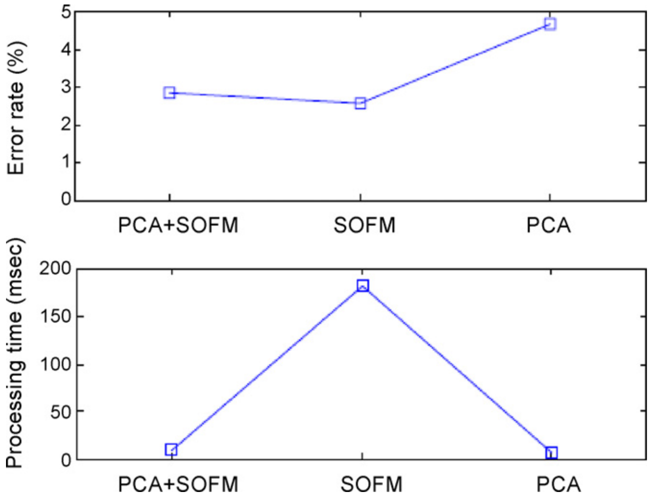

Fig. 10. Improvement of classification by applying the SOFM method [5].

Chu et al. [5] presented an extension to the feature projection method used by Englehart et al. [1]. They pointed out that applying PCA prevents a separation of class distribution, and the density functions of classes are not clearly discriminated. To overcome this problem, a linear–nonlinear feature projection composed of PCA and a self-organizing feature map (SOFM) was suggested. It included two functions: dimensionality reduction, and nonlinear mapping. Nonlinear mapping by SOFM transforms PCA-reduced features to a new feature space, with an improved capability of class separation. As a result, the classifier could find a hyper-plane with an enhanced separation margin. This scheme improved classification performance compared to using only PCA (Fig. 10). Applying PCA before SOFM was necessary due to real-time constraints. Therefore, the load of offline computation was extended into the wavelet packet transform, the eigenvectors of the covariance matrix for PCA, and finally the weight vectors of SOFM.

Englehart et al. [2] switched from time-scale features into time-domain features, using Hudgins's feature set in continuous classification. They reasoned that time-scale features were selected in Ref. [1], because of their temporal characteristics of a transient signal; while continuous classification works based on a steady-state signal, and focuses mainly on signal energy. It was shown that time-domain features outperform time-scale features, when a steady-state signal is processed using continuous classification. In addition, Chan et al. [19] by reproducing Hudgins' experiments [31] showed that slope sign changes (SSC) do not improve classification performance and even cause it to deteriorate.

Hussein and Granat [20] proposed using a time-scale-based technique for myoelectric signal feature extraction, that decreases global delay time, and improves time spectral analysis. It is called the Gabor matching pursuit (GMP) method, and is used in time-scale analysis, to provide an efficient estimation of a signal approximated by a linear combination of basic functions that are called an atom. In the proposed method, atoms are selected from a Gabor dictionary, and parameters computed by matching a pursuit procedure. In classification, the parameters of the atoms are interpreted as signal features. Although GMP is named as a successful method for non-stationary signal analysis, it suffers from computational complexity. Therefore, the authors applied a genetic algorithm (GA) to tournament selection, aiming to decrease normalized root mean square error (MSE), between the original and reconstructed signal. The algorithm simplifies the complexity associated with the classical method, in which an iterative process is based on selecting the largest inner product of the signal with a Gabor wavelet. The modification is to encode the parameters of each atom, and reduce the normalized root mean square error (NRMSE) associated with them. Features were classified using neuro-fuzzy classifiers; experimental results verified the performance of the proposed method.

4.2.2. Time domain and frequency domain features

Vuskovic and Du [15] applied a novel feature for myoelectric classification. It is the square of a signal processed by a moving average finite impulse response (FIR) filter, with a hamming windowing function of 300 ms. The resultant smooth waveform reflected a limb's dynamics in the form of a high amplitude oscillation. The maximum amplitude of a first oscillation was selected as a signal feature. It was empirically shown that the applied feature gave a good classification-hit rate. The long length of segment could be named as a drawback for this feature.

Du and Vuskovic [47] also had a comparative investigation in using a term of energy in time and frequency domains to recognize myoelectric patterns. Signal energy plays a major role in the success of classification, because it shows directly the level of muscle activation. Referring to Parceval theorem, energy can be defined either in a time or frequency domain. In a time domain, it is represented using the Integral Square of a signal during observation period (T_S):

$$E = \int_0^{T_S} x(t)^2\,dt = \sum_{n=0}^{N-1} x[n]^2, \quad N = \frac{T_S}{\Delta t}$$

As well as a frequency domain, it is equal to the zero-moment of a signal in a pre-defined bandwidth W. $P(f)$ is the power spectrum density (PSD) of a signal, and can be estimated using the periodogram:

$$E = M_0 = \int_0^{W} P(f)\,df, \quad P(f) \approx \frac{1}{N}\left|\sum_{n=0}^{N-1} x[n]\,e^{-j2\pi fn}\right|^2$$

Due to frequency leakage, an input signal is often windowed, i.e. $x[n]$ is replaced with $x[n]w[n]$, where $w[n]$ is a time windowing function such as a hamming window. With reference to Parceval theorem, it can be shown that the signal energy in the frequency domain can be calculated in the same way as the time domain, using a multiple windowing technique. This means that the signal energy for window "i" is obtained using:

$$M_{0i} = \sum_{n=0}^{N-1} (x[n]w[n-n_i])^2$$

Literature [47] introduces multiple trapezoidal windowing, and a short-time Thompson transform for feature extraction; in time and frequency domains, respectively. Both outperform the other considered features in classification performance. A trapezoidal window is offered for signal windowing, because a hamming window destroys energy information at the beginning and end of each window. In addition, a Thompson transform is preferred to a periodogram, since it generates the maximum concentration of energy, and reduces significantly spectral leakage and variance over a short segment length. As a conclusion, literature [47] suggests using multiple trapezoidal windowing on a raw signal in a time domain, over a short-time Thompson transform (STTP) in a frequency domain; since this provides much better time efficiency, and a lower dimension, with only a slightly smaller classification-hit rate.

Huang et al. [3] compared three groups of features in myoelectric classification. The groups were Hudgins' time-domain (TD) features, autoregressive (AR) coefficients, and signal root mean square (RMS). Results show that a combination of RMS with a six-order AR coefficient, yields higher performance. AR + RMS and AR + RMS + TD, result in a 3.7% and 3.1% average error rate, for six-class of limb motions, respectively. The feature vector in the later is too high. Furthermore, the combination of AR + RMS has been used by Chan and Englehart [18] and produced a high classification rate (about 94.63%).

Chaiyaratana et al. [10], Lamounier et al. [11], and Karlik et al. [13], also used AR coefficients as a feature set for myoelectric classification in prosthesis control. They referred to recursive least squares (RLS), a discrete Hopfield network (DHN), and PARCOR, as three algorithms that are mostly used in AR coefficient computation. RLS is based on the principle of minimizing the error between estimated and actual values of a signal. This algorithm is very reliable, and has the capability to deal with noisy signals. The extension of RLS algorithms to accommodate multivariable AR models is proposed such that all parameters of AR models from different signal channels can be computed simultaneously. A discrete Hopfield network (DHN) algorithm is used under the principle of multivariable optimization; its convergence rate of computation is higher than that of the RLS algorithm.

Karlik et al. [13] presented AR coefficients obtained by the PARCOR algorithm as signal features. These features were then clustered for different arm motions, using a fuzzy C-means algorithm, and finally applied to a neural network for classification. A rate of 98% was obtained for a six-class motion classification problem. An N-order AR model represents the correlation between N samples of signal. Therefore, it estimates the components of an original signal that have a frequency lower than a $1/N$ sampling frequency. In other words, a six-order AR model can represent a power spectrum 0–250 Hz of a signal, which is sampled with a sampling rate of 1500 Hz. This is an acceptable range, because the power spectrum of a myoelectric signal is mainly located between 10 and 250 Hz.

Ajiboye and Weir [4] applied the root mean square (RMS) of a signal, as a feature to a fuzzy logic classifier, in multifunctional prosthesis control; it yielded an overall classification rate between 94% and 99%. RMS in the transient and steady states of a signal is an acceptable maximum likelihood estimator of amplitude, and has been suggested as a myoelectric signal feature (because it provides physiologically significant information about the average power of muscles). Park and Lee [9] evaluated the performance of six features, an integrated absolute value (IAV), a difference absolute mean value (DAMV), variance (VAR), an autoregressive model (AR), linear cepstrum coefficients (LCC), and an adaptive cepstrum vector (ACV), in myoelectric classification. IAV, DAMV, and VAR, are from time-domain features, AR and LCC are spectral features, and finally ACV is selected to represent the non-stationary property of a signal. AR, LCC, and ACV features, demonstrate accurate information about a signal power spectrum and its characteristics. The authors applied a measure of class separability to evaluate the feasibility of features. The measure was provided based on a Bhattacharyya distance, which is principally used as a measure of the separation of classes:

$$\mu\left(\frac{1}{2}\right) = \frac{1}{8}(M_2 - M_1)^{\mathrm{T}}\left\{\frac{C_1 + C_2}{2}\right\}^{-1}(M_2 - M_1) + \frac{1}{2}\ln\frac{|(C_1 + C_2)/2|}{\sqrt{|C_1||C_2|}}$$

where μ is the separation measure, and (M_1, C_1) and (M_2, C_2), are the mean and covariance of classes 1 and 2, respectively. With regard to the obtained results, ACV was relatively the most feasible feature for signal classification.

5. Classification

Extracted features need to be classified into distinctive classes for the recognition of desired motion patterns. Due to the nature of myoelectric signals, it is reasonable to expect large variation in the value of a particular feature. Furthermore, there are external factors, such as changes in electrode position, fatigue, and sweat, which cause changes in a signal pattern over time. A classifier should be able to cope with such varying patterns optimally, as well as prevent over fitting. Classification should be adequately fast, in order to meet real-time constraints. A suitable classifier has to be efficient in classifying novel patterns; online training can maintain the stably of classification performance over long-term operation.

5.1. Neural networks approach

Many literatures highlight the success of neural networks in myoelectric classification. The main motivation for neural networks has stemmed from a desire to use artificial intelligence (AI) to implement tasks via learning. The advantage of the neural network is its ability to represent both linear and nonlinear relationships; and learn those relationships directly from data being modelled. It also meets real-time constraints, which are an important feature in control systems. As pioneers in developing real-time pattern recognition-based myoelectric control, Hudgins et al. [31,32] used a multi-layer perceptron (MLP) neural network to classify time domain features. It was capable of classifying four types of limb motion, with an error rate of around 10%. Recently, Zhao et al. [30] applied an MLP neural network to recognise six motion patterns based on signal time-scale features and entropy, and met an average accuracy of about 95%.

Englehart et al. [1] compared linear discriminate analysis (LDA) with MLP neural networks, as a myoelectric classifier. It was observed that LDA performed similar to or better than MLP for time-scale features; which were dimensionally reduced using PCA. This presumably, is because PCA (applied for dimension reduction), has the effect of linearization on feature sets. The LDA classifier is also much simpler to implement, and much faster to train than MLP. Chaiyaratana et al. [10], and Lamounier et al. [11], applied MLP and RBF neural networks for myoelectric classification, respectively. The cost function of an MLP network is defined as

$$\varepsilon(n) = \frac{1}{2}\sum_{i=1}^{N} e_i(n)^2, \quad e_i(n) = d_i(n) - y_i(n)$$

where $d_i(n)$ and $y_i(n)$ are the desired and actual output of the ith output node of a network, respectively. The weights were calculated using back propagation (BP) algorithms (in order to minimize the cost function). The cost function of an RBF network is

$$\varepsilon(n) = \frac{1}{2}\sum_{i=1}^{N} e_i(n)^2, \quad e_i(n) = d_i(n) - \sum_{j=1}^{M_i} w_{ij}(n)\ \exp[-(x - t_j)^{\mathrm{T}} C_j^{-1}(x - t_j)]$$

where x, t_i, C_j, are the input pattern, jth centre of the radial basis function, and jth covariance matrix, respectively. A steepest descent algorithm was used to determine network weights.

Au and Kirsch [16], developed a time-delayed artificial neural network (TDANN), which was fed a raw signal, rather than features to predict the kinematics variables of a shoulder and elbow. TDANN was capable of characterizing any linear and nonlinear relationship between input signals and output variables. In addition, the time-delayed input signal allowed TDANN to capture the dynamics of input signals, which were mostly highlighted in spectral analysis such as an AR model. TDANN is trained via back propagation, until the sum of the squared errors (SSE) between its output and actual kinematics variables drop below a threshold. The structure of TDANN is shown in Fig. 11. The numbers of layers and neurons, as well as the number and duration of delays used in inputs were determined empirically based on experiments. The literature suggests that a two-layered TDANN with 20 neurons in the hidden layer has 875 ms total delay, with 125 ms between delayed inputs for joint angles, 625 ms total delay, and 125 ms between delayed inputs for velocities and accelerations.

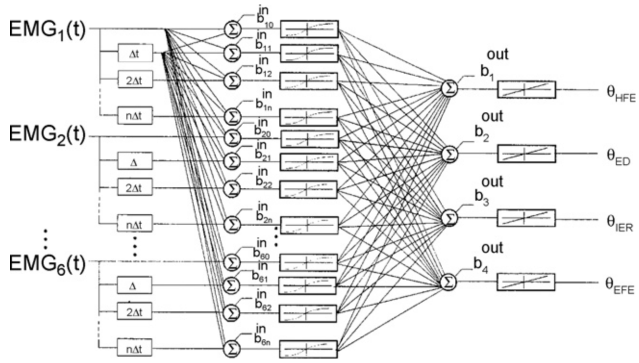

Fig. 11. Structure of the time-delayed ANN applied in Ref. [16].

5.2. Fuzzy approach

There are many advantages to using fuzzy logic systems for bio-signal processing and classification. Bio-signals are not always strictly repeatable, and may sometimes even be contradictory. Fuzzy logic systems tolerate remarkable contradictions in data. Fuzzy systems are able to discover patterns in data that are not easily detectable. Furthermore, in fuzzy logic approaches, medical expert experience can be incorporated in processing and classification. It is possible to integrate this incomplete but valuable knowledge into a fuzzy logic system, because of its reasoning style. Fuzzy approaches exploit tolerance of imprecision, uncertainty, and partial truth; to achieve tractable, robust, and low-cost solutions for classification.

Ajiboye and Weir [4] used a heuristic fuzzy logic approach to multi-channel myoelectric pattern recognition, based on a simple vernacular language that is easily understood, quickly and automatically generated for any user, and executed in real time, with a response time of 45 ms. The main advantage of this system is its simplicity. The proposed classifier (the same as in classic fuzzy systems), consists of three parts: an input membership function (iMBF), an inference rule base (IRB), and an output membership function (oMBF). The iMBF fuzzifies numerical inputs by converting them into linguistic variables. The IRB performs classification by processing linguistic inputs, returning linguistic outputs, and associating a degree of truth. The oMBF defuzzifies linguistic outputs by converting them into numerical values. The iMBF converts a signal feature into four grades of signal (i.e. OFF, LOW, MED, HIGH), as shown in Fig. 12. The IRB, the brain of the fuzzy system, consists of weighted vernacular language rules in an IF-THEN form. The number of rules in an IRB depends on the different patterns presented within training data. Rules are generated automatically using a fuzzy C-means (FCM) algorithm applied to data during training. It seeks to cluster data together, in order to minimize the variance between data in the same cluster, and maximize the variance between data in different clusters. Clustering allows data to be shown based on the centre of clusters; these represent the rules in an IRB. All data can belong to all clusters, with a degree of membership (DOM) in each cluster in the interval [0, 1]. The DOM is directly related to the Euclidean distance between each data sample and cluster

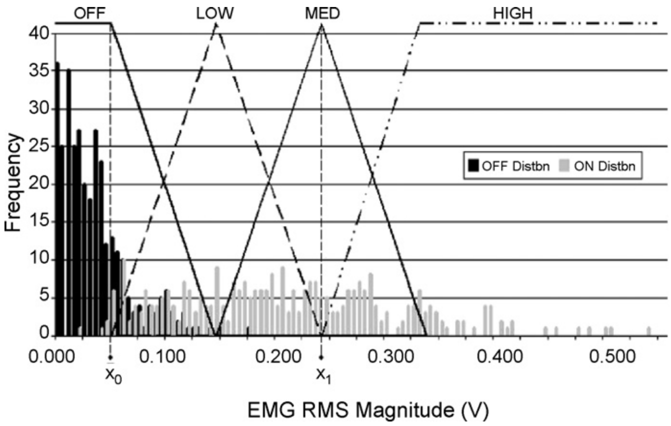

Fig. 12. MES histogram used to construct input membership functions [4].

centre. The rules are processed in parallel, and the results then passed to the oMBF for defuzzification, using a standard mean-of-maximum (MoM) algorithm.

Park and Lee [9] adopted an evidence accumulation (EA) method for classification, i.e. using Dempster–Shafer theory of evidence to estimate intended motion from a myoelectric signal. In this method, four components, namely: evidence for (ef), evidence against (ea), neutral evidence (n), and contradictory evidence (x), were used to represent the evidence of an event. Each component was a number in the range [0, 1]. The accumulation of evidence for a class is illustrated in Fig. 13. Notations a, b, c, ... represent signal features such as IAV, DAMV, VAR, AR, LCC, and ACV. The class that has the maximal ''evidence for'' (ef), is chosen as the motion class corresponding to the input signal. The components of evidence are determined using a fuzzy mapping function, applied to the distance between signal features and reference parameters obtained during a training period. The literature claims that reasonably accurate results are generated, with less computing time and little subject training.

5.3. Neuro-fuzzy approach

Kiguchi et al. [7,8] applied a neuro-fuzzy controller to control an assistant exoskeleton system; which assisted a user's motion for daily activity and rehabilitation using a myoelectric signal. The controller is a combination of a flexible fuzzy controller, and an adaptive neural network (Fig. 14). Its input variables are the mean absolute value (MAV), of signals collected from 11 muscles, elbow angle, shoulder angles (vertical and horizontal), and wrist force. Output variables are the torque command for the shoulder, desired impedance parameters, and the desired angle for an elbow. Two evaluation functions evaluate the error between desired and actual values of angles and myoelectric signals. The support of an exoskeleton is adjusted until the myoelectric signal approaches its desired level; which is selected for each user based on his/her physical and physiological condition. Initial IF-THEN rules are designed based on pre-experiments that analyze elbow and shoulder motion patterns; these are then translated into neural network form. There are 16 rules for elbow motion, 32 rules for shoulder motion, and 2 rules for switching between myoelectric and wrist force sensor-based control.

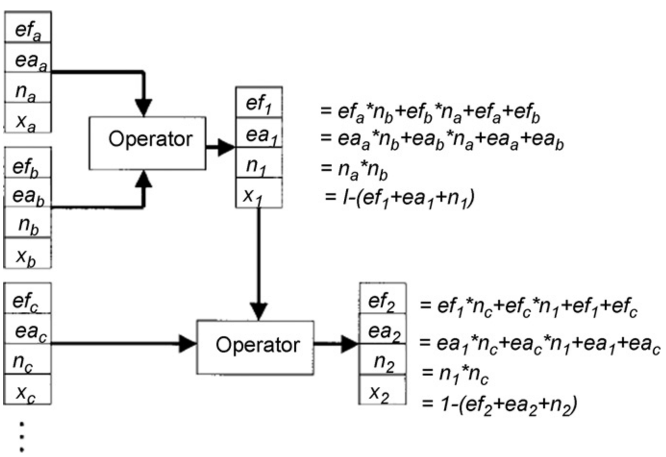

Fig. 13. Evidence accumulation procedure [9].

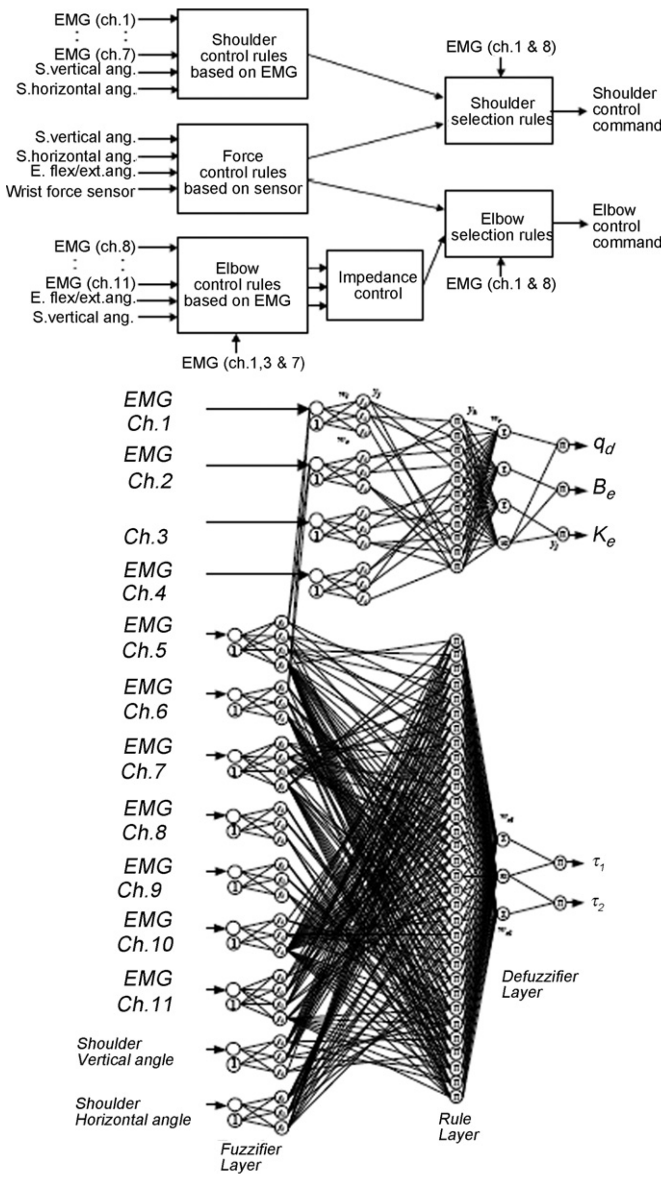

Fig. 14. Structure of a neuro-fuzzy controller [7].

Karlik et al. [13] presented a fuzzy clustering neural network (FCNN) for classification. Fuzzy clustering assigns data to overlapped clusters with a certain degree of membership (DOM). It means that for each feature vector x_k, a variable $0 \leq u_{ik} \leq 1$ can be defined to quantify its membership to a cluster with a centre v_i. To implement fuzzy clustering, an algorithm is proposed that minimizes the cost function J_m:

$$J_{\mathrm{m}} = \sum_{k=1}^{N}\sum_{i=1}^{C}(u_{ik})^m ||x_k - v_i||_A^2$$

where A is used to define the distance between x_k and v_i.

The literature also employed a conic section function neural network (CSFNN) as a classifier. CSFNN allows decision surfaces to be adapted between open boundaries as in MLP, and closed ones as in RBF; providing unification between RBF and MLP. Its propagation rule, which is comprised of both RBF and MLP propagation rules, is given by

$$y_j = \sum_{i=1}^{N+1}(x_i - c_{ij})w_{ij} - \cos\ \omega_j \sqrt{\sum_{i=1}^{N+1}(x_i - c_{ij})^2}$$

where w_{ij} represents the weights in the MLP, and c_{ij} represents cluster centres in the RBF neural network. The propagation rule includes two major parts: the first part is made up of MLP propagation rules, and the second the Euclidean distance analogous to RBF. ω_j determines the ratio of each network in a CSFNN. A comparative assessment in Ref. [13] shows more reliable results are obtained using FCNN than MLP and CSFNN. It has been demonstrated that the training time of FCNN is approximately half the time required for MLP. CSFNN, with a rate of 88%, has no satisfactory classification performance in comparison to MLP and FCNN, which have a rate of 97% and 98%, respectively.

Vuskovic and Du [15] suggested a modified version of a simplified fuzzy ARTMAP network for myoelectric classification; and pointed out that such an approach is very efficient and robust in terms of sensitivity to the size and ordering of patterns, and offers incremental training. ART is a binary unsupervised neural network that is based on adaptive resonance theory (ART). It is able to acquire new patterns without forgetting previously trained patterns. Fuzzy ARTMAP is an extension that can be applied for supervised classification of binary and analogue patterns. The proposed modification is based on using the Mahalanobis distance, in activation and matching functions. This results in a significant reduction in output nodes, and produces faster training and classification. With regard to experimental classification applied to grasping patterns in Ref. [15], the modification yields a higher classification rate.

Chan et al. [19] proposed a fuzzy approach to neural networks for myoelectric pattern recognition. A three-layer feed forward network as depicted in Fig. 15 represents the proposed system. fz_{ji} is the Gaussian fuzzifier function. It resembles, but differs from a RBF neural network. In this fuzzy network, the centre, width, and weights, are updated using back propagation; while it merely updates the weights in the RBF networks. The centre and width represent the fuzzifier, and weights represent the fuzzy rules. The structure of the fuzzy classifier for an N-class problem was composed of N parallel subsystems, similar to those shown in Fig. 15. Every subsystem generates the activation level for each motion. The class estimated by the classifier was selected based on the maximum output of subsystems. Basic ISO-data initialized the fuzzy rules before the training phase. The literature concluded that the training process and classification performance of the proposed fuzzy approach were superior to those of neural network-based approaches, with more consistent classification non-sensitive to over-training. A 95% classification performance was achieved using this fuzzy system when time domain features were applied.

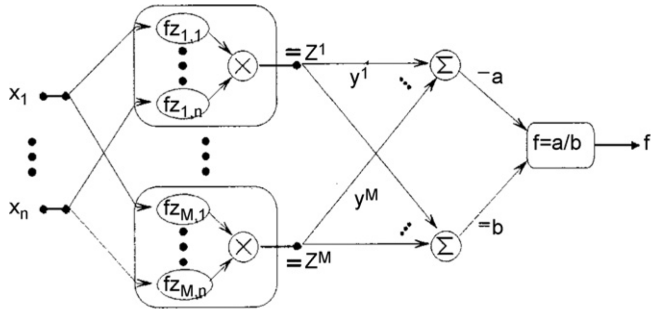

Fig. 15. Structure of a fuzzy subsystem and Gaussian fuzzifier [19].

Han et al. [33] applied fuzzy min–max neural networks (FMMNN) as a classifier to adapt the variation of a signal; because of its online adaptation function. A supervised learning neural network utilized fuzzy sets as a pattern. Each fuzzy set was a combination of fuzzy hyper-boxes. A fuzzy hyper-box is an N-dimensional box defined by min and max points, with a corresponding membership function. It is used as an input–output pair for learning.

5.4. Probabilistic approach

Since a myoelectric signal is stochastic, probabilistic approaches that are based on the probability of each class may outperform other classification approaches. A Gaussian mixture model (GMM) is a probabilistic approach that has been used in pattern recognition. It has the ability to form a smooth approximation for general probability density functions, via the weighted sum of multiple Gaussian functions. GMM not only provides a smooth overall distribution fit, its components can, if required, clearly detail a multimodal density. It has shown remarkable performance in many applications, such as text and speech recognition, and has been a dominant tool in pattern recognition.

Huang et al. [3] demonstrated the potential of a Gaussian mixture model (GMM) in myoelectric classification. It was built upon preliminary work done by Chan and Englehart [17], to optimize a GMM for limb motion classification. N-GMM was developed to specify the probability of each class in an N-class problem. The probability density of GMM, which is called mixture density (MD), is a linear combination of multiple standard Gaussian probability densities (named components); they are parameterized by a set of weights, mean vectors, and covariance matrixes of the components. The model that generates the highest probability determines the predicted class. The goal of training is to estimate the parameters of GMM at which the mixture density will best match the distribution of the training set. Parameters were estimated using an expectation maximization (EM) algorithm, wherein GMM in Ref. [3], linear discriminate analysis (LDA), multi-layer perceptron (MLP), and linear perceptron (LP) neural networks were used as a classifier to compare their performance. Classifiers were cascaded using MV post-processing in a continuous classification scheme. GMM's performance matched, or exceeded other classifiers with a 96.3% classification rate; using AR + RMS features for the six-class problem.

Fukuda et al. [14] also used GMM for a human-assisting manipulator that was tele-operated using a myoelectric signal. The classifier known as a log-linearized Gaussian mixture network (LLGMN) was directly applied to a raw signal, rather than signal features. A LLGMN is capable of discriminating stochastic signal patterns with nonlinear and non-stationary characteristics. It is a constructed neural network based on GMM, which outputs a posterior probability for each motion class. Moreover, a suspension rule and online training were proposed to stabilize the performance of classification when controlling the system over the long term. More explanation about online training is provided in the next section. A LLGMN was preferred to back propagation-based neural networks, because it includes a pre-organised structure, and can model the complicated mapping between input patterns and discriminating classes; even for a small sample size. It also outperforms maximum-likelihood neural networks that are based on GMM. The structure of a LLGMN with three layers is shown in Fig. 16.

A hidden Markov model (HMM) is another probabilistic approach to myoelectric pattern recognition. Chan and Englehart [18] showed that a HMM approach provides even better accuracy than MLP; while maintaining intuitive control and a fast response time. A Markov chain topology in HMM, consists of states and state transition probabilities. Associated with each state is an observation probability density function, which accounts for the probabilistic nature of the observed data. State observation is generated based on signal features. Outputs of HMM indicate the probability of each state, and the highest probability determines the intended motion. HMM state observation probabilities are assumed as single Gaussian densities. Since an initial state and state transition matrix are selected preliminarily and fixed, training is only limited to the computation of the mean vector and covariance matrix of the Gaussian probability of state observation. In general, HMM provides considerable promise in multifunction myoelectric classification. It has high classification accuracy, and low computational cost, which make it an attractive choice in real-time systems. The low computational overhead associated with training an HMM, also enables the possibility of adaptive classifier training while in use.

5.5. Online training

The characteristics of collected surface myoelectric signals vary with time, and make every pattern recognition-based control system face exponentially rising error over long-time operation. The main reason for this is that signal patterns used for training differ increasingly with current patterns after a period, and consequently the accuracy of classification drops notably. Online training, in which a classifier is trained continuously using new patterns during operation, makes the rate of accuracy stable. Changes emanating from physiological factors, such as sweat and fatigue, exhibit gradual changes or physical factors, such as electrode displacement. Therefore, online training seems intensively inevitable for long-term operation.

There are two crucial issues in online training. The former is the recognition and updating of valid online training data, and the later applying a training algorithm during operation. Training data, i.e. input–output, requires clarification as to whether classified patterns coincide with user intention. Therefore, input–output pairs must be monitored and evaluated continuously to update training data. In addition, applying a training algorithm to a classifier during operation requires a distinguished method.

Fukuda et al. [14] used entropy as a measure for the validity of input–output pairs. It was defined as

$$E(i) = \sum_{n=1}^{N} O_n(i) \log(O_n(i))$$

The literature pointed out that if entropy developed as a result of input, $x(i)$ is less than a certain threshold, the reliability of the classified pattern seems to be high, and pairs $[x(i), O(i)]$

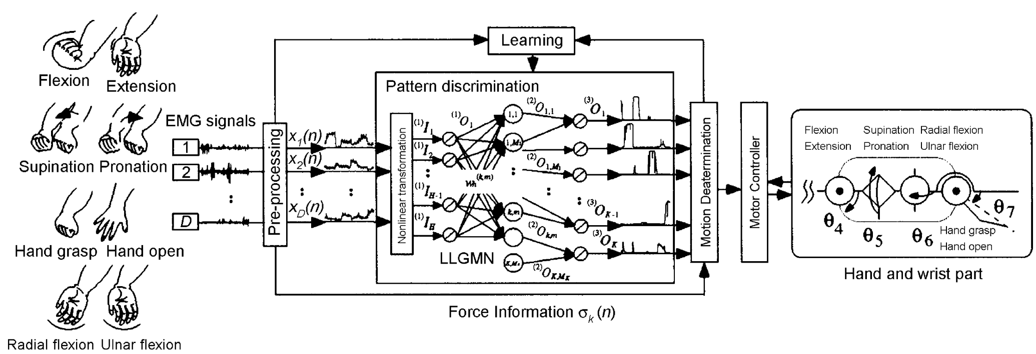

Fig. 16. MCS in the hand-wrist part of a human-assisting manipulator [14].

can be added to the online training set, and the oldest one deleted. Network weights are then updated based on the new training set. If the energy function of the network does not decrease during early iterations of online training, weights would not be updated to avoid incorrect training. This means that weights are modified gradually, and classification does not degrade suddenly. Moreover, a classification suspension rule suspends the operation as entropy in output exceeds a pre-specified threshold, because large entropy means that output commands are ambiguous. In this way, network entropy is continuously monitored.

Kato et al. [48] presented an approach for online training to adjust to gradual and drastic changes in myoelectric signal characteristics. It was mainly focused on training data management, and consisted of three functions: automatic elimination (AE), automatic addition (AA), and selective addition (SA) of training data. AE and AA judge discrimination state by monitoring outputs during operation, and adjust to gradual changes by eliminating or adding training data. The judging criterion is the continuity in output, and is based on the hypothesis that a motion command cannot be interchanged in less than a given time. SA also makes a system adjust to drastic changes by adding new training data based on a user's selection. For automatic elimination/addition, an input–output pair is accompanied by a variable that shows the degree of contribution in classification. It is quantified based on the time interval of continuity of commands. The time interval is compared with a failure and success threshold, i.e. 220 and 800 ms, respectively.

Fuzzy ARTMAP is a neural network that has the potential to be used in online training. It supports incremental training, while back propagation is naturally a batch oriented training method. ART networks are typically plastic and stable, which means that they are able to learn new knowledge, and retain previously learnt knowledge. They are fast and easy to train, and can generally achieve better accuracy over a smaller number of processing nodes. A modified version of fuzzy ARTMAP as discussed formerly, was proposed in Ref. [15] as a classifier for myoelectric signals.

6. Non-pattern recognition-based myoelectric control

Non-pattern recognition-based myoelectric control includes proportional control, threshold control, onset analysis, and finite state machines. The number of functions that can be controlled by non-pattern recognition-based controllers is limited in comparison to pattern recognition-based controllers. They have a simple structure, and have mostly been deployed in ON/OFF control or navigation. In proportional control, the strength of muscle contraction controls speed or force. It can be used in conjunction with either pattern recognition-based, or non-pattern recognition-based methods, to allow precise positioning and accurate force control. ''Finite state machine'' and ''onset analysis'', are two non-pattern recognition-based controllers that will be discussed in this section. Fig. 17 depicts a schematic diagram of their structure. As can be seen, the classification module of a pattern recognition-based controller has been degraded to a simple threshold comparison module.

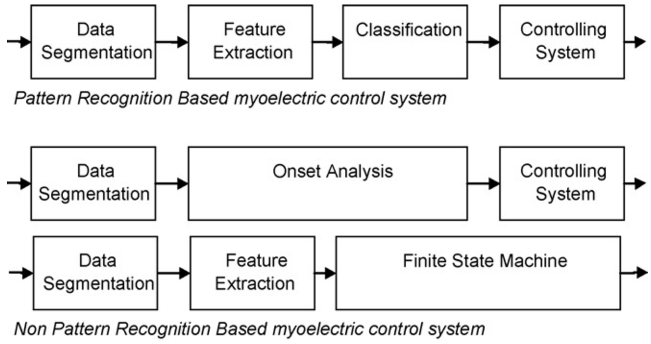

Fig. 17. A non-pattern recognition-based myoelectric control system.

6.1. Onset analysis

Muscle activation or deactivation is presented using temporal characteristics, such as onset time, offset time, and reaction duration; and has the potential to be used as a reference control signal. Fig. 18 depicts a pulse signal (c), generated based on a myoelectric signal: (a) using onset analysis, and (b) using post-processing methods. In this section, different approaches to onset detection will be reviewed. The performance of onset detection methods is mainly evaluated based on the bias and variance of estimated onset time, as well as sensitivity to SNR.

The single-threshold method is a primary and simple phenomenological approach. In this method, rectified raw signals are compared with thresholds that are obtained based on the mean power of background noise. It is very fast and simple in implementation, but too sensitive to SNR. It suits coarse ON/OFF detection rather than slowly increasing muscle activities. An improved single-threshold method is based on a time enveloped signal, rather than its instant value. For example, the mean absolute value of a low-pass filtered signal is compared with a threshold that relates to noise. Due to time delay in computing, filters cause bias in estimated onset time. An improved single-threshold method is not well suited to standardization, since its performance depends intensively on signal envelope and threshold. Signal mean value, low-pass filtered signal mean value, and Marple–Hovart and Gilbey (MHG) [6] algorithms, are popular members of the improved single-threshold method.

In an MHG algorithm, two adjacent windows equal in length (leading and trailing), slide over a sequence of data. In each leading window, the mean absolute value of a signal is calculated and compared with the signal in the trial window. Onset and offset time can be obtained by relying on the hypothesis that the maximum difference between mean values occurs when one window contains a muscle contraction, and the other does not. Sun et al. [6] introduced a maximum value detection (MVD) algorithm based on a bipolar model of onset detection. In the MVD algorithm, a muscle is assumed in an excited state if there is a peak greater than a given threshold within a certain segment length. This segment length is

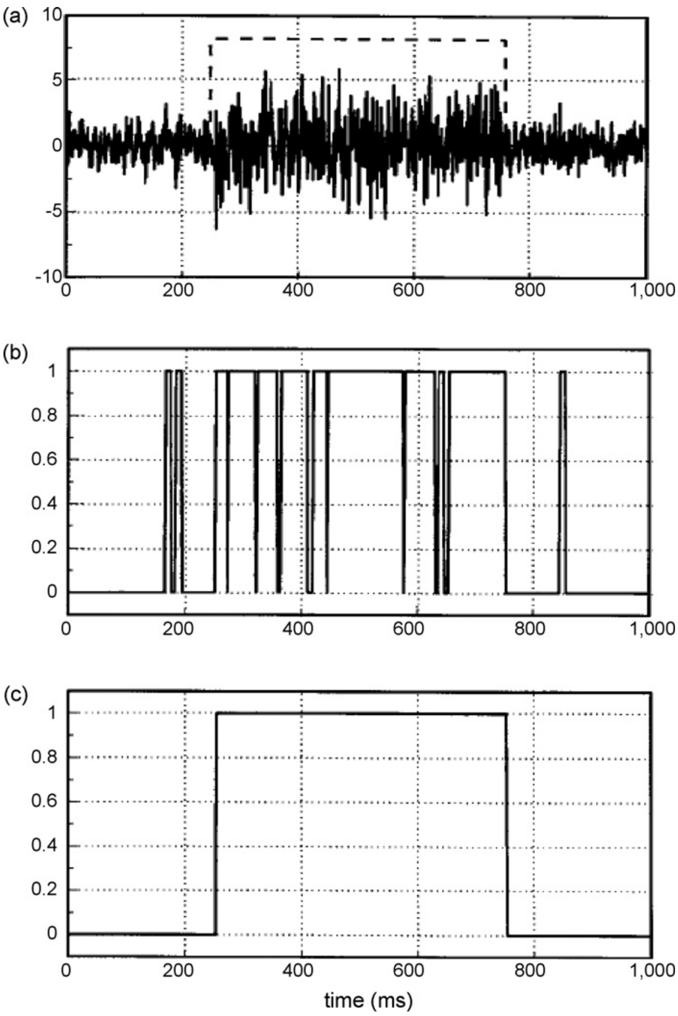

Fig. 18. ON–OFF timing for muscle contraction detected by a double-threshold method [41]: (a) simulated MES signal, (b) output of the detector, and (c) output of the post-processor.

influenced directly by the distance between electrodes, and conduction speed in tissues.

In the double-threshold method proposed by Bonato et al. [41], single-threshold detection is applied to a fixed number of consecutive values of an auxiliary variable, and onset is detected when at least a certain number of them cross the threshold. Therefore, the false-alarm probability (which is the probability that noise samples are incorrectly interpreted as signals), and detection probability (which is the probability that signal samples corrupted by noise are correctly recognised), as well as time resolution (which shows the length of an observation window), can be adjusted independently. The double-threshold method is superior to single-threshold ones, because it involves more parameters to tune. It yields a higher detection probability for a fixed value of false-alarm probability in comparison to the single-threshold method, and in addition, a user can adapt the link between the two mentioned probabilities with a higher degree of freedom. Bonato et al. [41], succeeded in achieving a bias lower than 10 ms, with a standard deviation lower than 15 ms, on simulated signals with an 8 dB SNR. To reject wrong transitions during onset

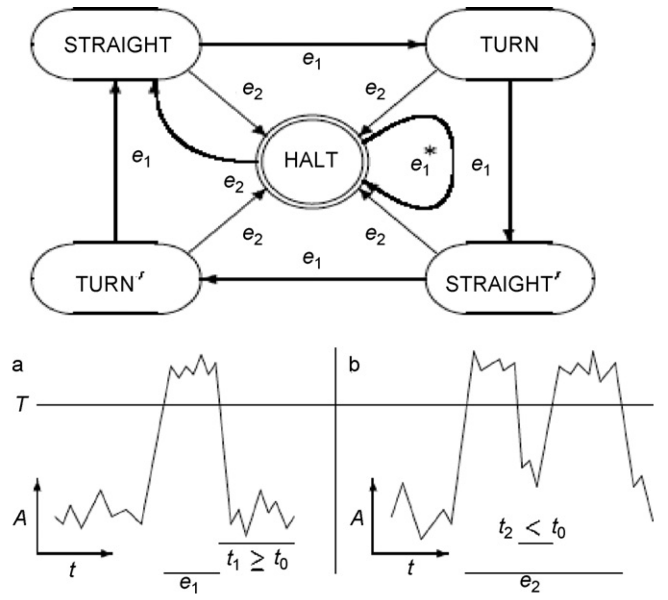

Fig. 19. A state transition diagram and detectable events from MES in wheelchair control [29].

detection, a post-processor was cascaded to the detector; this rejected any transition shorter than 30 ms. The output of the detector and post-processor are shown in Fig. 18.

Merlo et al. [24] proposed an approach to estimate muscle ON/OFF timing based on a physical model of muscle activation. This approach is based on the detection of single MUAP from a synthetic signal, using a continuous wavelet transform (CWT). The maximum output of the matched filters obtained by CWT at different scales, was compared with a

Left EMG	Right EMG	State	Command
on	on	0/1	Stop / Go forward
on	off	2	Turn left
off	on	3	Turn right
off	off	4	Preserve / Go forward

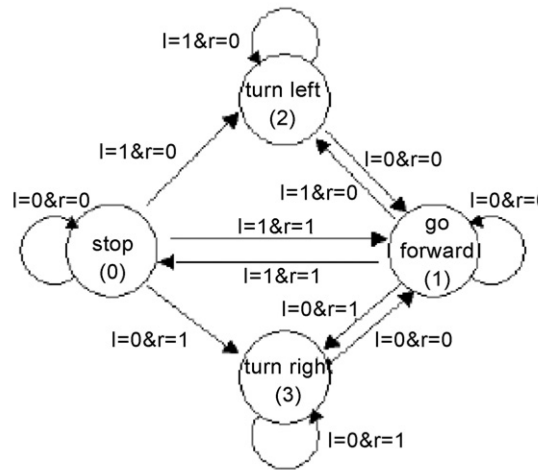

Fig. 20. A state definition and transition for wheelchair myoelectric control [34].

certain threshold to detect muscle activation. A mathematical model was used to test the proposed technique on synthetic signals. The resultant bias of onset detection was lower than 40 ms, and the standard deviation lower than 30 ms, in the case of non-whitened Gaussian noise with an SNR as low as 2 dB. This method was notably fast, and well suited for real-time implementation.

6.2. Finite state machine approach

Finite state machine (FSM) outputs, pre-define commands based on sequences of input signals. They are composed of a finite number of states, transition between those states, and commands. Like a classification module, they need to be tuned before operation; by defining states, state transition roles, and output commands. States often represent pre-defined motion commands for an assistive robot, and transition roles are associated with raw signal or signal features.

Felzer and Freisleben [29] applied a FSM to drive a wheelchair based on myoelectric signals collected from forehead skin. The process consisted of four basic steps: (i) analysis of an input signal, (ii) determination of a next state, (iii) display a next state, and (iv) issuance of an output command. The first step is responsible for converting input signals into a stream of certain events that keep tracking states. Signal amplitude is monitored. If it exceeds the threshold once, the event of a ‘‘single click’’ (e_1) is registered, and if it exceeds twice within a pre-defined time interval between the event, a ‘‘double click’’ (e_2) is registered, as shown in Fig. 19. The order of detected events turns the current state into one of the pre-defined states: LEFT, RIGHT, STRAIGHT, and HALT. A state diagram illustrating the respective transitions is shown in Fig. 19. To evaluate the performance of a myoelectric controller, the time elapsed to drive a wheelchair at a constant speed, but in different routes and distances, was recorded and compared with traditional joystick-based controllers. As expected, the myoelectric control is slower, but the overhead time less than 50%.

Moon et al. [34], employed an FSM to manipulate a wheelchair based on shoulder elevation gestures. They proposed the double-threshold method on MAV (of myoelectric signals collected from left and right shoulders), to recognise user intention. In the proposed method, the primary and auxiliary thresholds were compared concurrently with signal features. The auxiliary threshold was smaller than the primary, and each condition, between primary and auxiliary threshold, was considered the reserve condition that kept the pervious state in state transition. The state definition and state transition diagram of an FSM used by Moon et al. [34], is shown in Fig. 20. It shows that the

Table 1
Applications of myoelectric control

Reference	Application	Class	Channel	Classifier	Feature
Hudgins et al. [31]	Upper limb prosthesis	4-class motion	2-channel	MLP NN	MAV, MAVS, ZC, SSC, WL
Englehart et al. [1]	Upper limb prosthesis	6-class motion	4-channel	PCA/LDA	STFT, WT, WPT
Huang et al. [3]	Upper limb prosthesis	6-class motion	4-channel	GMM/MV	RMS, AR
Kiguchi et al. [7,8]	3-DOF assisting exoskeleton	6-class motion	11-channel	Neuro-fuzzy network	MAV
Fukuda et al. [14]	human-assisting manipulator	8-class motion	6-channel	LLGMN (online training)	–
Vuskovic and Du [15]	Finger joints control	6-class motion	4-channel	Simplified fuzzy ARTMAP network	
Carrozza et al. [35]	Prosthetic hand (1-DOF)	2-state	2-channel	FSM	–
Felzer and Freisleben [29]	Powered wheelchair	5-state	Forehead muscle	FSM	–
Han et al. [33]	Powered wheelchair	4-state	Near neck muscles	Fuzzy min–max neural networks (FMMNN)	IAV, VAR
Moon et al. [34]	Powered wheelchair	4-state	Shoulder elevation gestures	FSM	MAV
Lamounier et al. [11]	mechanism to train patients to work with myoelectric prosthesis	4-class motion	5-channel	MLP NN	AR
Barniv et al. [26]	virtual environment (VE) to eliminate latencies		8-channel	PCA/ICA MLP NN	MA, ZC, etc.
Nilas et al. [28]	Morse code-based commands for human-assisting or rehabilitating robots	8-class motion	2-channel		MA
Ju et al. [25]	User interface for portable consumer electronics	4-class gestures	2-channel	HMM	AR
Au and Kirsch [16]	Functional Neuromuscular Stimulation (FNS) in a paralyzed shoulder and elbow	8-class motion	6-channel	TDANN	
Christodoulou and Pattichis [12]	To diagnose neuromuscular disorders		Unsupervised single-channel biceps muscle	ANN SOFM, LVQ	
Khalil and Duchêne [23]	Characterizing events in uterine MES for preterm birth	4-class events		DCS	WT

elapsed time to manipulate a simulated wheelchair in a complex trajectory, increases by about 50% when using myoelectric control.

7. Potential applications

Prosthesis is the most important and only commercial application of myoelectric control systems. Hand, forearm, and fingers are the main limbs, and wrist and elbow are the joints that myoelectric prostheses could resemble in motion. The ''Utah Arm–Elbow'', ''LTI Boston Arm'', and ''Otto Bock Arm–Elbow'', are currently available myoelectric prostheses. They are microprocessor based, and can be programmed for different motions. In additon, numerous literature in the past 15 years has shown potential application for myoelectric control, in grasping, wheelchair control, virtual reality, and gesture-based user interfaces. Some of these are summarized in Table 1.

Application of pattern recognition-based myoelectric control has not had remarkable improvement, despite many laboratory-based advances, as highlighted in this survey. The reasoning behind this fact is a controversial issue, which may lead to lines of research in the future. The lack of an interactive and bi-directional interface between a controller and device, is an important weakness. In intact limbs, internal feedback that is adequately fast (i.e. touch), helps a user to adjust muscle contraction in fine control, which myoelectric control cannot perform. Another weakness of myoelectric control is the lack of individual control on some of muscles, even on intact limbs. Making the distinguishable contraction for all muscles, usually needs alot of exercise, and sometimes is impractical. This prevents fine control in multi-function devices. Finally, the necessity to concentrate and continuously physically react during manipulation is the other weakness of myoelectric control. Although the necessity to concentrate is expected to decrease with practice, it is likely this would take a long time, and it is possible that the prostheses/robot may have been abandoned by the user before this was achieved.

Developing high precision and fast feedback between device and controller, would improve the quality of control and dexterity. Feedback that passes through the mind is not too fast, and would impose a mental burden that would create problems during daily work. Since motions and contractions shape the set of sequences in normal limb trajectories, motion sensors on the limb can provide useful feedback during myoelectric control. Data fusion applied to myoelectric signals and limb motion sensors, are capable of providing a reliable closed loop control system.

8. Conclusion

A surface myoelectric signal is formed via the summation of individual action potentials generated by irregular discharges of active motor units in muscle fibers. It contains rich information that can make myoelectric control a pioneer solution for rehabilitation devices and human-assisting robots. The level of activity of muscles, either in static contraction or in dynamic limb-motion, is the most important factor to be recognized in myoelectric control. Therefore, applying time domain features that represent the term of energy in a myoelectric signal, such as MAV and RMS, can result in significant performance; as well as a reletively low computing load. Spectral and time-scale features not only show the level of activation in muscles, but also have the capability to signal de-noise (particularly in fatigue mode), however they have a high computing load cost.

The achievements discussed in this paper, have led to the development of new strategies for the improvement of multifunction myoelectric control. In respect of this, increasing the number of sites to collect signals, and applying sensory feedback is suggested. Since limb motions emanate from the concurrent activation of several small and large muscles, collecting data from different sites on the skin involves more muscles in classifciation, and improves the number of functions that a controller can manipulate. It also improves accuracy, by providing more discriminative patterns for input signals for each motion. Using more input sites for a signal, increases accuracy more than applying a combination of complex features. Therefore, developing wearable electrodes that contain a matrix of electrodes, can provide many input signals for classification. To cope with dimensionality, a subset selection approach, which is proposed by the authors in Ref. [46], is suggested. Moreover, employment of sensory feedback, along with a myoelectric signal, can provide complementary input patterns for a classifier to discriminate more accurately and intiutively. Sensory feedback can be generated by a residual part of a limb in injured or disabled people. A sensor-data fusion approach is also sugessted for handling both myoelectric and feedback signals.

A state machine performs reliable control for navigation, such as in powered wheelchair control; but for multifunction control purposes, pattern recognition-based myoelectric controllers are essential. Due to the stochastic structure of a myoelectric signal, probabilistic approaches such as GMM can play an effective role in classification. Continuous segmentation, along with majority voting as a post-processing mechanism, improve remarkably, accuracy and response time. Online training and output evaluation, provide stable accuracy to guard against probable changes during long-term operation. Developing multi-threaded algorithms that can handle operation and training concurrently, is intensively recommended to guarantee stable performance. Finally, classification methods that use a combination of binary classifiers, such as a support vector machines applied for multiclass classification, are recommended. This is because the presence or non-presence of activity in each muscle, associates input patterns with limb motions.

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