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Myoelectric signal processing for control of powered limb prostheses

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Abstract

Progress in myoelectric control technology has over the years been incremental, due in part to the alternating focus of the R&D between control methodology and device hardware. The technology has over the past 50 years or so moved from single muscle control of a single prosthesis function to muscle group activity control of multifunction prostheses. Central to these changes have been developments in the means of extracting information from the myoelectric signal. This paper gives an overview of the myoelectric signal processing challenge, a brief look at the challenge from an historical perspective, the state-of-the-art in myoelectric signal processing for prosthesis control, and an indication of where this field is heading. The paper demonstrates that considerable progress has been made in providing clients with useful and reliable myoelectric communication channels, and that exciting work and developments are on the horizon.

Keywords: Myoelectric; Signal; Processing; Prostheses; Communication; Control

1. Introduction

Control systems for powered upper limb prostheses often use the surface myoelectric signal as the control input. This control approach, referred to as myoelectric control, has been a clinically significant option for limb-deficient individuals for some 30 years. In these systems voluntarily controlled parameters of the signal from a muscle or muscle group are used to select and modulate a function of a multifunction prosthesis. Fig. 1 shows a block diagram schematic of the essential elements of a myoelectric control system. The feedforward path is the myoelectric channel, which is a replacement in part for the physiological motor control system. The effectiveness of myoelectric control continues to improve, offering users improvements in dexterity and ease of use.

The indications for myoelectric control include upper limb amputation, appropriate control signal sites, i.e., superficial voluntarily controlled muscle, and suitable life-style and functional requirements, i.e., function required can be met with externally powered devices. The number of amputees per year that could be considered candidates for myoelectric control is difficult to ascertain, however, it is estimated to be in the order of 10,000 per year in the USA. The acceptance of a controller by the client depends on a number of factors including client motivation, control complexity, and system reliability. For an in-depth discussion of powered upper limb prostheses, see Mazumdar (2004).

Myoelectric signal as control input has dominated because it has several advantages over other inputs. Namely that the user is freed of straps and harnesses, the signal is noninvasively detected on the surface of the skin, the muscle activity required to provide control signals is relatively small and can resemble the effort required of an intact limb, it can be adapted to proportional control with relative ease, and the required electronic circuits (whether analog or digital) can be continuously improved and miniaturized and they appear to have the prospect of better long-term reliability.

Myoelectric control improvements over the years have been incremental in nature. This is due in part to the alternating nature of myoelectric control R&D between control

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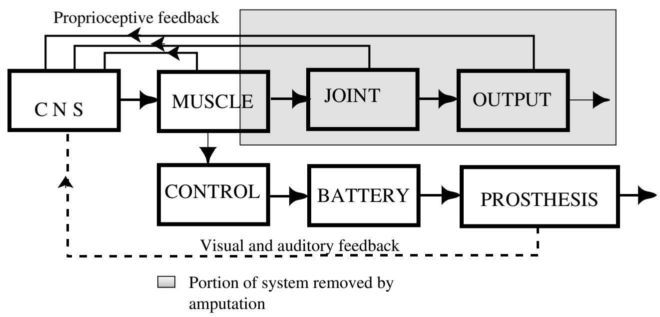

Fig. 1. Block diagram illustrating relationship between normal and myoelectric control systems (shaded area is removed by amputation). (Reprinted from Parker and Scott (1986) with permission.)

algorithms and device hardware. On the one hand the need for more sophisticated control algorithms increases with the device functionality, while on the other more functional devices are only useful if the algorithms for control are available. The functionality requirement of the prosthesis increases with the level of amputation, which leads to a paradox seen in myoelectric control. Namely that the functionality and thus control site requirements increase with the level of amputation while the number of sites decreases and these sites are less physiologic (the muscle normally involved in the function is used as the control source).

As implied in the previous paragraph the primary engineering issues in myoelectric control are the mechanical design of multifunction devices (hands, wrists, elbows, etc.), and the design of appropriate signal processing algorithms for these devices. Given the demand for increased prosthesis functionality and progress in device capability, a major R&D thrust to obtain continuous simultaneous independent multifunction controllers is on. The objective of this paper is to provide an overview of myoelectric signal processing in the context of the past, current, and future directions in prosthesis control.

2. The myoelectric signal processing challenge

While the overall task is control of the prosthesis, it is appropriate to think of the feedforward path as a communication channel in which the myoelectric signal becomes an information carrier. The control information is encoded by modulating some feature/features of the signal, as discussed later. In this context, the myoelectric signal processing problem becomes one of demodulation, and an appropriate demodulation algorithm is required to recover the control information, as shown in Fig. 2.

The user of a channel modulates the carrier through motor unit recruitment and firing rate patterns. The modulation manifests itself in signal parameters such as variance or mean absolute value (MAV) as well as in signal patterns such as time-frequency or autoregressive moving average (ARMA) model parameters. Thus, parameter and pattern detection/estimation are at the heart of a myoelectric channel demodulator for prosthesis control.

A channel includes the muscle group, the volume conductor between each muscle of the group and the electrode, and the summing electrode. The block diagram for a linear system model for a channel is given in Fig. 3 where for the ith muscle, $i = 1, \ldots, m$, S_i is the muscle electrical source, $U(t,\lambda_i,p_i)$ is the pooled innervation point process with pooled firing rate λ_i and pattern p_i, $P(t,r_i)$ is the average motor unit action potential seen at the electrode with distance r_i from the source, and $m_i(t)$ is the ith muscle signal.

The parameters of $M(t)$ that can be voluntarily modulated are the recruitment parameters λ_i through muscle contraction level, and to some extent the p_i through variations in muscle contributions. It can be shown (Parker et al., 2004) that for the quasi-isometric contractions

$$\sigma_m^2 = \sum_{i=1}^{m} k_i \lambda_i \tag{1}$$

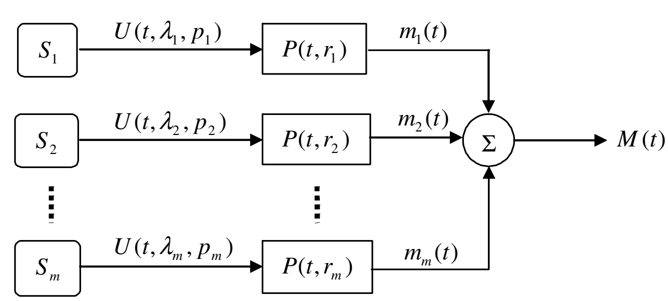

Fig. 3. Linear system model for a myoelectric channel consisting of muscle sources, S_i, innervation processes, $U(t,\lambda_i,p_i)$, and volume conductor filters, $P(t,r_i)$, $i = 1,2,\ldots,m$. (Reprinted from Parker et al. (2004) with permission.)

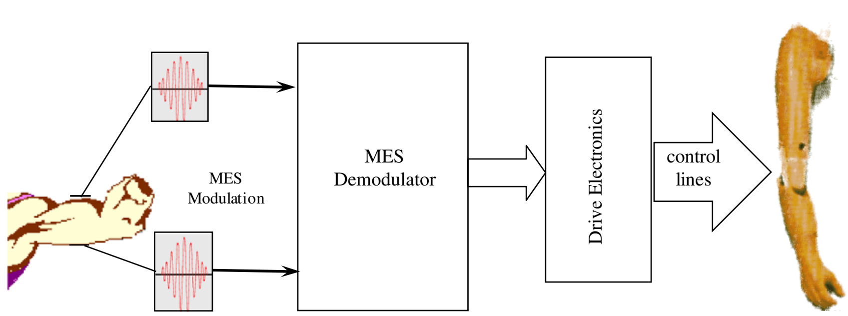

Fig. 2. Myoelectric communication channel.

and for nonstationary contractions

$$\sigma_m^2(t) \approx \sum_{i=1}^{m} k_i \lambda_i(t), \quad (2)$$

where σ_m^2 is the variance of $M(t)$, and k_i is a muscle constant.

Thus, it is seen that voluntary modulation of the λ_i through muscle contraction level provides voluntary modulation of the variance, σ_m^2, of $M(t)$. Voluntary modulation of the variance is the basis of conventional myoelectric control systems such as the three-state controller (Dorcas and Scott, 1966). For reviews of amplitude modulation-based controllers, see Parker and Scott (1986) and Scott and Parker (1988). The modulation of signal, $M(t)$, parameter patterns through λ_i and p_i, $i = 1,2, \ldots, m$, is the basis for more recent multifunction controllers (Hudgins et al., 1993; Englehart et al., 1999). Detailed reviews of pattern classifier-based systems are given in Hudgins et al. (1994) and Englehart et al. (2001a). All myoelectric communication channel demodulators have the task of recovering/estimating these parameters and/or parameter patterns.

With reference to Fig. 4, performance measures for the communication channel are typically demodulator function classification rate (probability of error), and operator error. As pointed out in Englehart and Hudgins (2003) these might not well reflect prosthesis functionality in which case an active daily living (ADL) assessment is required (Lock et al., 2005). The challenge for myoelectric channel design is to maximize functionality and performance while minimizing complexity and response time.

What is it about the myoelectric channel that makes signal processing for prosthesis control such a challenge? There are two principal reasons. The first has to do with demodulator output signal-to-noise ratio (SNR) where signal and noise are the demodulator's output mean and standard deviation, respectively – see Fig. 5. Unlike the mechanical force output at the muscle tendon where the SNR is large (>10) and increases with the number of active motor units, the SNR of the myoelectric channel demodulator is relatively low (<10) and does not increase with the number of motor units beyond about 10 (Parker and Scott, 1986). Specifically, SNR can be shown, (Parker et al., 2004), to be given for MAV by SNR = $(4BT)^{1/2}$, where B is the signal equivalent statistical bandwidth (≈100 Hz) and T is the demodulator response time. The demodulator SNR will in large part determine the classification performance, and it can be seen that T is the only design parameter through which the SNR can be affected. A typical value for B is 100 Hz, and a value of 250 ms for T gives an SNR of only 10. Thus, there is a tradeoff between demodulator performance and dynamic response. It is generally accepted that T should in practice not exceed 200 ms.

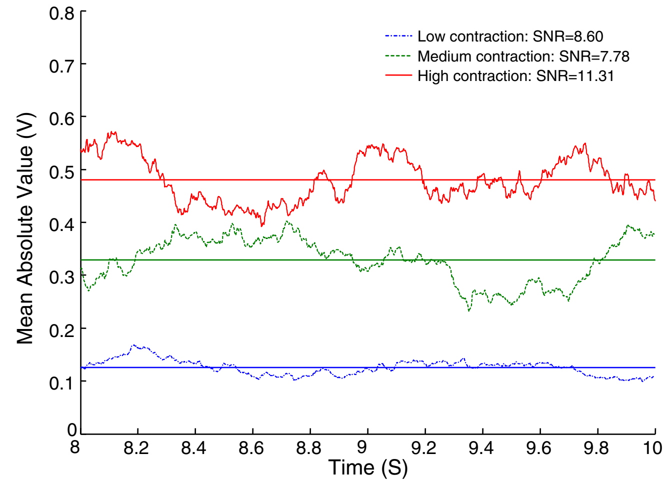

Fig. 5. MES mean absolute value (MAV) estimate at three different contraction levels. MAV estimated with a 250 ms rectangular averaging window.

The second reason is the difficulty presented to the prosthesis user of generating correct signals at the channel input. For the amputee this will be without the benefit of full proprioceptive feedback. Incorrect signals presented to the channel produce output errors (referred to as operator error) even if the demodulator's classification is correct. Operator error rate has been found to be acceptable in the case of conventional three-state amplitude modulation controllers and in some multifunction controllers using higher dimension signal pattern modulation.

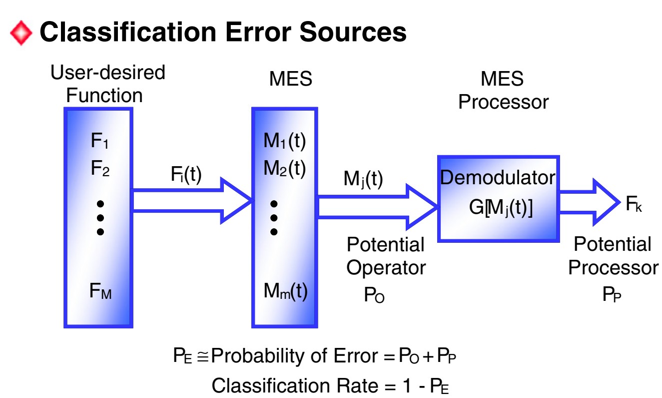

Fig. 4. Sources of classification error.

3. Historical perspective

Early, pre-1960s, myoelectric communication channels used two-state amplitude modulation and envelope demodulators (Berger and Huppert, 1952; Reiter, 1948) and were limited clinically by the electronics technology of the period. With the development of semiconductor device technology and the associated decrease in device size and power requirements, clinical application saw promise and research and development increased dramatically.

During the 1960s and 1970s significant progress was made in the development of myoelectric signal amplitude and rate modulation for multistate controllers. Two-state amplitude- or rate-modulated channels (see Fig. 6) were the first to receive R&D attention (Battye et al., 1955; Bottomley, 1965; Herberts, 1969; Jacobsen and Mann, 1973;

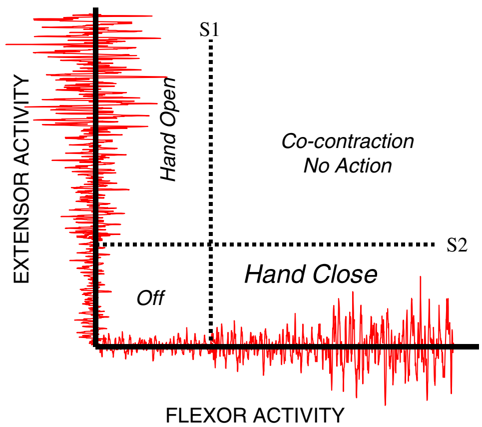

Fig. 6. Example of two-state amplitude modulation for control of a hand. S1 and S2 are switching thresholds for flexor and extensor activity, respectively. (Reprinted from Parker et al. (2004) with permission.)

Kato et al., 1967; Kobrinski, 1960; Lyman et al., 1976; Schmidl, 1977; Vodovnik et al., 1967) and the first to be taken up commercially by such companies as Otto Bock, Hugh Steeper, Motion Control Inc., Liberty Mutual, Variety Ability Systems, and Fidelity Electronics. These systems are attractive as they are physiologic and hence easy to use, and have very good performance. On the other hand, each function requires a muscle control source, the availability of which decreases as the amputation level increases. To address this limitation three-state amplitude-modulated channels (see Fig. 7) were developed (Childress, 1969; Dorcas and Scott, 1966) and taken up commercially by such

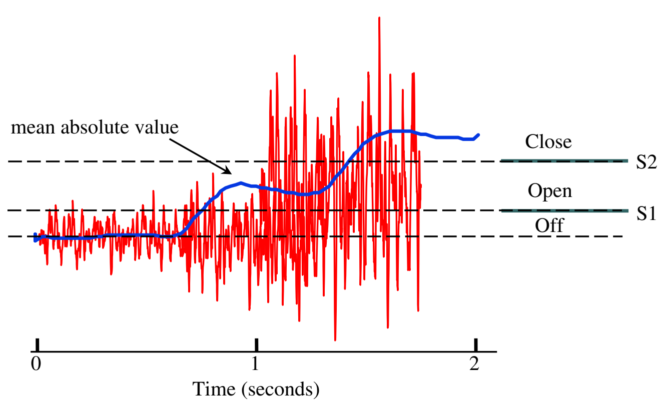

Fig. 7. Example of three-state amplitude modulation for control of a hand. S1 and S2 are switching thresholds for flexor and extensor activity, respectively. (Reprinted from Parker et al. (2004) with permission.)

companies as Otto Bock, Hugh Steeper, Hosmer, and Fidelity Electronics. These systems, in which each muscle source can control two functions, are not physiologic and hence not as easy to use although with a brief training period the performance is good (Richard et al., 1983; Paciga et al., 1980). It is also shown that, for amplitude-modulated channels with more than three states, the operator error is unacceptable.

The period 1975 to the present saw large improvements in performance (>90%) for multifunction (>2) control through application of new approaches including optimal detection/estimation, pattern recognition, and electrode arrays. Fig. 8 shows a block diagram of the general demodulation/classification process for the multifunction controller. For classification purposes a set of MES features must be selected, for example, time-domain statistics, short-time Fourier transform (STFT) values, wavelet transform values, etc. This feature vector can, in general, be of very high dimension in which case dimension reduction techniques such as feature selection or feature projection are applied in order to reduce the classification complexity. Possible classifiers include Bayes, linear discriminant analyzer (LDA), and multilayer perceptron neural network (MLP), each of which has its advantages and disadvantages.

In multifunction systems using a single myoelectric channel with amplitude modulation improved demodulation performance was obtained through the application of optimal signaling and detection methods (Bayes classifier) (Parker et al., 1977) and parameter estimation methods (Hogan and Mann, 1980). Signal amplitude modulation and detection is a pattern recognition-based controller in which the classifier's feature vector is one-dimensional. In order to obtain acceptable classifier performance with more than three functions and still one channel, pattern-based systems using more than one signal parameter (feature vector dimension >1) were developed. Graupe and Cline (1975) were among the first, using four parameters of an ARMA model of steady-state signal with a "nearest neighbor" classifier to classify four functions with a performance > 95%. Hudgins et al. (1993) developed a four-function system using four time-domain parameters of transient signal with an adaptive neural network (ANN) classifier as shown in Fig. 9. After off-line training of the ANN the classifier coefficients are downloaded to a microprocessor-based on-line controller. A performance, averaged over limb-deficient and normally limbed users, of 85% was obtained.

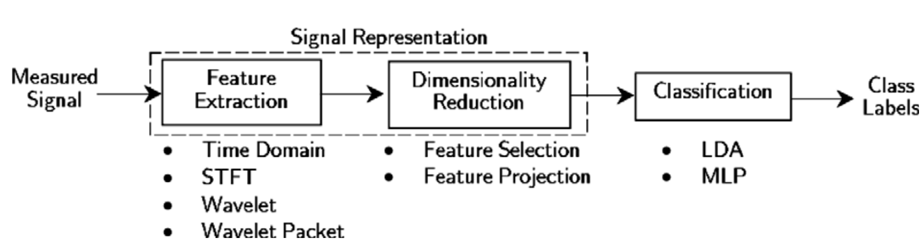

Fig. 8. A breakdown of the classification problem, and the possible methods applicable to each block. (Reprinted from Englehart et al. (1999) with permission.)

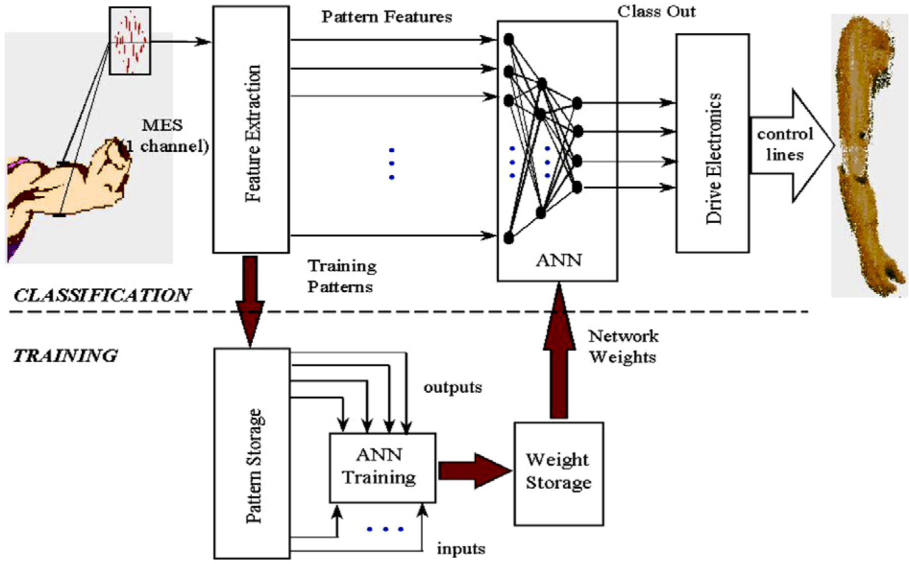

Fig. 9. A multifunction control scheme based upon the transient MES, using an artificial neural network. (Reprinted from Englehart et al., 2001a with permission.)

The previous paragraph described performance improvements in the single-channel multifunction system through an increase in feature vector dimension. Improvements can be also be obtained through and increase in the number of channels. One of the earliest of this case is the work of Finley and Wirta (1967), who used six channels of amplitude modulation with a ''linear discriminant'' classifier to obtain a performance > 80% with a six-function system. Lyman et al. (1976) used nine channels for three degrees of freedom with amplitude modulation and a ''nearest neighbor'' classifier. Almstrom et al. (1981) obtained a 90% classification rate with amplitude modulation of six channels for six functions using a linear discriminant classifier. Saridis and Gootee (1982) developed a two-channel system with a Bayes classifier of signal moments for six functions and 85% classification. Doershuk et al. (1983) used four channels with four ARMA coefficients per channel to classify four functions with a ''nearest neighbor'' classifier and >95% classification. Kuruganti et al. (1995) used two channels with five time-domain features per channel to classify four functions with an ANN classifier and 90% classification. Englehart et al. (2001b) used four channels with wavelet coefficient features and an ANN to classify six functions at 98% classification.

The contributions for this period can be summarized as: (1) the optimization of MES parameter detection/estimation, (2) the application of MES temporal and spatial patterns, (3) the development of signal pattern feature selection and reduction, (4) the application of trainable classifiers, and (5) the application of electrode arrays and muscle group signal patterns.

4. State of the art

Commercially available myoelectric control systems use combinations of one-channel two-state and one-channel three-state communications with amplitude or rate modulation/demodulation. These systems are well developed, reasonably reliable, and for the most part provide the performance that clients require for the available prostheses hardware. However, with the recent developments in multifunction prostheses hardware there has been considerable effort towards providing improved multifunction (>2) control.

The ultimate goal of this development work is to have simultaneous, independent, and proportional control of multiple degrees of freedom with acceptable performance (classification rate and ADL) and near ''normal'' control complexity and response time. The thrusts in R&D towards this end have been in a number of directions. First, to improve multifunction performance while maintaining or reducing control complexity, is extending the signal pattern work through the classification of signal parameter patterns generated by an electrode array detecting multiple signals from a muscle group – a multichannel approach. The different patterns are generated by normal movements associated with the muscle group. Davidge et al. (2004) investigated the extent of increase in classification performance with number of channels – see Fig. 10. The performance in classifying 10 functions with a linear discriminant (LD) classifier increased with number of channels, reaching 94% at 16 channels. However, the performances at eight and four channels drop to only 93% and 87%, respectively.

The second thrust, aimed at reducing control complexity for the user, is to develop multifunction pattern classification and control algorithms which allow the user to generate the patterns via normal movements (virtual movements in the case of an amputee), and which can be ''trained'' to optimize performance for a given user. This approach is becoming standard, and can be readily realized through microprocessor-based Bayes, ANN, and LD classifiers. The classifier is trained off-line with a PC and the resulting

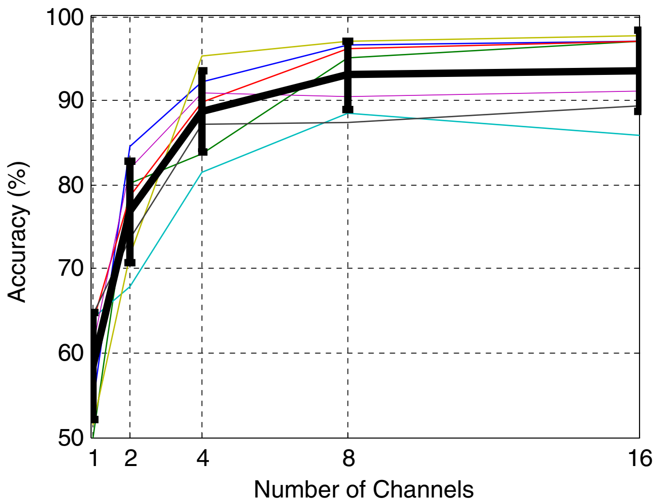

Fig. 10. Classification results of discrete motions using autoregressive model coefficients and RMS value as features and an LDA classifier. The heavy black line is the mean over six subjects and the error bars indicate one standard deviation of the data.

coefficients downloaded to the microprocessor – see Fig. 9 and Hudgins et al. (1997).

With this approach the classifier can be easily retrained if necessary, and indeed the signal processing strategy can be quickly modified. Englehart and Hudgins (2003) developed a real-time processor around this approach. Their classification performance using four channels in a four-class problem with a LD classifier, as a function of processor delay and data analysis window, is shown in Fig. 11.

Another thrust is to obtain a "continuous" controller (Englehart et al., 2001b) in which the signal modulation can move from function to function without first going to the "rest" function. This is desirable from the user's point of view as it is more efficient and results in a seamless function transition. A relatively new and promising

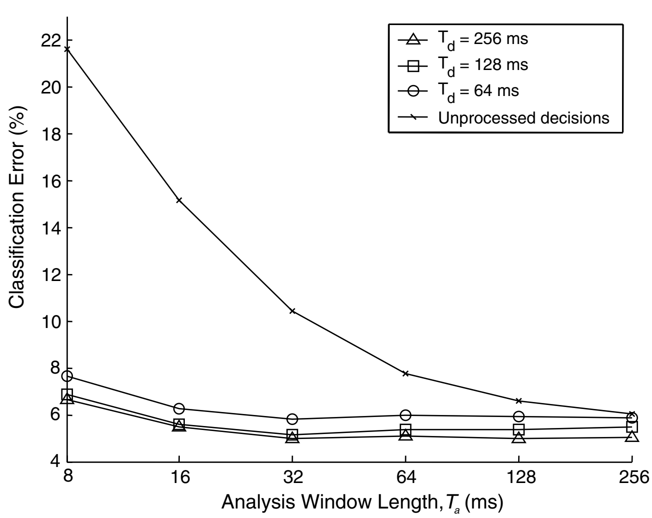

Fig. 11. The effect of analysis window length, T_a, and the acceptable delay, T_d, upon the classification accuracy of the system. The error is expressed as a percentage, averaged over all 12 subjects. (Reprinted from Englehart and Hudgins (2003) with permission.)

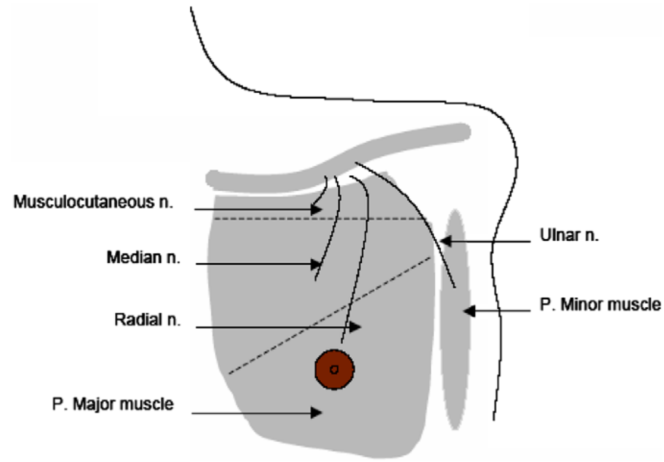

Fig. 12. Targeted reinnervation on shoulder disarticulation patient. (Reprinted from Miller et al. (2005) with permission.)

approach (Chan and Englehart, 2005) to the continuous controller uses a hidden Markov model (HMM) as the classifier. The HMM classifier is well suited to the myoelectric channel because of its resilience to temporal variations. It was found that the performance with a four-channel six-function system exceeded that of an MLP ANN classifier and it also handled the function transitions with less error.

A major constraint on current myoelectric controllers is not only that the number of signal sources decreases with level of amputation but also that the sources that are available are mostly not physiologic. This clearly adds greatly to the control complexity, load on the user, and user training. However, in many cases the nerves that originally innervated the lost muscles and functions are intact – albeit truncated. An innovative approach to resolving this constraint, referred to as "targeted reinnervation" (Miller et al., 2005), is to surgically deinnervate some functioning muscle (say in the chest region) and reinnervate it with the truncated nerve. The reinnervated muscle can now act as a physiologic myoelectric source for control of a function lost due to amputation – see Fig. 12.

5. Future directions and expectations

There are a number of research directions towards meeting the stated goal of simultaneous, independent, and proportional control of multiple degrees of freedom with acceptable performance (classification rate and ADL) and near "normal" control complexity and response time.

To reach simultaneous, independent, and proportional control, two possible approaches might be taken – direct and pattern function selection. The direct approach entails a one-to-one mapping between a given channel activity and a given function. This requires a signal detection method that is immune to crosstalk between muscles. Most promising in this regard is the targeted reinnervation work described above together with the application of signal telemetry implants. An implantable system proposed by Weir et al. (2005) can be placed in the reinnervated muscle providing a control source that is both physiologic and immune to crosstalk – thus direct proportional control of a function. A number of such implants could provide the desired simultaneous, independent, and proportional control.

The pattern approach would have an electrode array detecting, from a group of muscles, signals with feature patterns that depend on the group co-activity. The co-activity pattern and feature set would map proportionally to a corresponding set of degree-of–freedoms (DOF). The proportional mapping would be established through the training of an ANN that has the same number of proportional outputs as the number of DOFs. Through the training the ANN learns which subset of DOFs are required and at what level of activation for the required limb movement.

An interesting and potentially effective approach to independent simultaneous control is independent component analysis and blind source separation. Applied to the signals generated by a group of muscles and detected by an array of electrodes, it is theoretically possible, under certain conditions, to recover the individual muscle signals for control purposes.

The USA Defense Advanced Research Projects Agency (DARPA) has initiated an R&D program to investigate novel neuromuscular interfaces for the control of prostheses. This very ambitious research program will look at control inputs from a mixture of peripheral nerve and myoelectric signals, as well as signals for proprioceptive, local, and supervisory feedback.

6. Concluding remark

Myoelectric signal processing for powered prosthesis control input has indeed come a long way, but still there are many challenges and exciting prospects for improvements!

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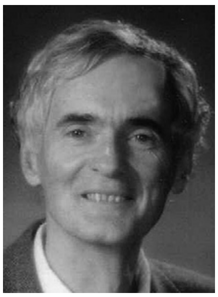

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