A New Strategy for Multifunction Myoelectric Control

Bernard Hudgins, Philip Parker, *Senior Member, IEEE*, and Robert N. Scott, *Senior Member, IEEE*

***Abstract*—This paper describes a novel approach to the control of a multifunction prosthesis based on the classification of myoelectric patterns. It is shown that the myoelectric signal exhibits a deterministic structure during the initial phase of a muscle contraction. Features are extracted from several time segments of the myoelectric signal to preserve pattern structure. These features are then classified using an artificial neural network. The control signals are derived from natural contraction patterns which can be produced reliably with little subject training. The new control scheme increases the number of functions which can be controlled by a single channel of myoelectric signal but does so in a way which does not increase the effort required by the amputee. Results are presented to support this approach.**

BACKGROUND

MYOELECTRIC systems have received widespread use as controls of prosthetic devices for individuals with amputations or congenitally deficient upper limbs [1], [2]. Many systems are now available commerically to control a single device (hand, elbow, wrist). These systems extract a control signal based on an estimate of the amplitude [3], or on the rate of change [4] of the myoelectric signal (MES). This control signal is either derived from a single myoelectric channel, in which case the amplitude of the signal is used to select one of three states of device operation, or it is derived from two channels of myoelectric signal, in which case the channel with the largest amplitude determines the device state. Once the state is selected its speed may be constant [3], or it may be controlled in a manner proportional to the level of myoelectric activity [5]. Although the success of fitting these systems for single device control is apparent, the extension to the control of more than one device (either simultaneously or sequentially) has been difficult. For this reason fittings of high level amputees often have been unsuccessful [2]. However, it is these individuals who would benefit most from the functional replacement of their lost limbs. The lack of success can be attributed primarily to the inadequacy of present multifunction control strategies.

To develop a practical multifunction myoelectrically controlled prosthesis it is necessary to extract more information from each channel of myoelectric signal, or to assign a control function to a specific combination of signals from a multichannel system. In this way, the number of control outputs or functions may be greater than the number of control inputs or channels. The number of functions per control channel of a level coded or rate coded system is limited to at most two [6]. An attempt to increse the number of states per channel by using state feedback has been unsuccessful [7]. Other multifunction prostheses have been developed using several channels of amplitude coding [8], [9]. These require the existence of several electrode sites which are usually difficult if not possible to locate on high level amputees. The Boston elbow [5] and Utah arm [10] have been used with some success in combination with an electric hand but this has required the use of a mechanical switching arrangement or a switch based on a quick co-contraction to select which of the two devices is to be controlled. More elaborate multifunction prostheses have been attempted but the result is that training the user to isolate the required number of control muscles is impractical if not impossible [11].

The myoelectric signal is essentially a one-dimensional pattern and the methods and algorithms developed for patten recognition can be applied to its analysis. The information extracted from the myoelectric signal, represented in a feature vector, is chosen to minimize the control error. In order to achieve this, a feature set must be chosen which maximally separates the desired output classes. The need for fast response of the prosthesis limits the period over which these features can be extracted. Once a feature set has been chosen, a suitable pattern classifier can be used to determine class output.

Numerous researchers have discussed attempts toward solving the multifunction myoelectric control problem using pattern recognition. All multifunction myoelectric control systems implemented using pattern recognition have been based on the assumption that at a given electrode location, the set of parameters describing the myoelectric signal will be repeatable for a given state of muscle activation and furthermore it will be different from one state of activation to another [12]. To control M functions in the prosthesis requires M unique patterns of activity. The control schemes have been based almost entirely on the discriminant approach to pattern recognition, in which each pattern is described by a set of N features. These features may be myoelectric signals from a number of channels, a set of statistics describing the signal sampled at one control site, or some other reproducible set of features. Once the patterns are described in this N-dimensional feature space an unknown pattern can be compared with them, in some way, to determine which of the M functions should be selected.

Multifunction control systems based on either the weighted sum of the mean absolute values [13]–[15] or other statis-

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The authors are with the Institute of Biomedical Engineering, University of New Brunswick, Fredericton, N.B., Canada E3B 5A3.
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tical measures [16]–[18] extracted from many channels of myoelectric signal share many of the same deficiencies of multichannel amplitude coded systems. Graupe developed an alternative pattern recognition scheme based on time series analysis of the myoelectric signal sampled from a single control site [12], [19], [20]. In essence he has replaced the information as obtained from the signal's mean absolute value at many sites with the many parameters of the stochastic temporal pattern of the signal at one site. Others have extended Graupe's work using a multichannel approach [21]. Kelly *et al.*has implemented a single channel multifunction control scheme based on the classification of myoelectric spectra using an artificial neural network. These single-channel systems required a relatively large computational effort and did not evolve beyond a laboratory implementation.

The purpose of the current work was to investigate new approaches to the problem of control of a multifunction prosthetic limb. The paper has two major sections. Section I describes new information found in the patterns of instantaneous myoelectric signal associated with the onset of a muscle contraction. Section II discusses implementation and evaluation of a single channel five-state proportional myoelectric control system based on the classification of these patterns.

Section I. Preliminary Study

Introduction

This section describes research undertaken to determine if more information can be extracted from a signal channel of myoelectric signal. The myoelectric signal measured at the skin surface should hold a wealth of information concerning the underlying muscle contraction. However, much of this information is neglected or obscured by the signal conditioners used in conventional myoelectric control systems. The section begins with a description of an experiment in which myoelectric signals from normally limbed and amputee subjects are collected during static and dynamic contractions of the arm. The results describe new information in the myoelectric signal found during the initial phase of a dynamic contraction. The section concludes with a discussion of how this information can be used to control a multifunction myoelectric limb.

Methods

Four normally limbed subjects and one above elbow amputee took part in this study. Myoelectric data were obtained from each subject during isometric and anisometric contractions. The signal was acquired using a single bipolar surface electrode pair. An active electrode was placed over each of the biceps brachii and triceps brachii muscle groups of each subject. This arrangement should provide the maximum pickup region for the acquisition of myoelectric signal from all muscles in the upper arm. A differential amplifier with an isolated input and signal gain of 5000 was used to amplify the myoelectric signal. The amplified myoelectric signal was sampled at a rate of 1 kHz using a Metrabyte DAS16F A/D board in an IBM PC/AT compatible microcomputer. A threshold based on the level of myoelectric activity was used to trigger sampling.

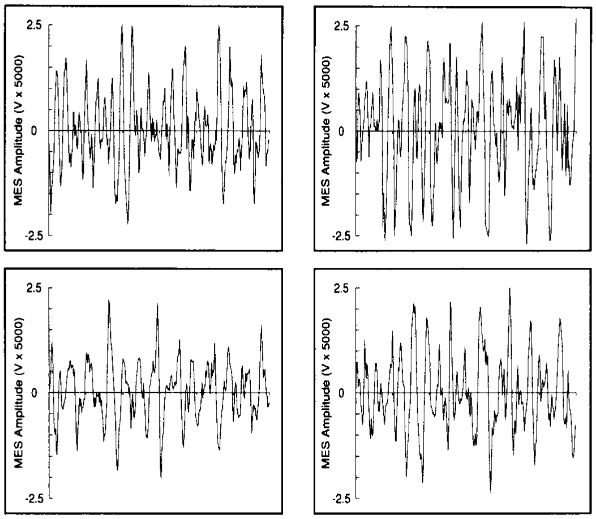
The subjects were first instructed to maintain a constant force isometric contraction and myoelectric data were acquired once the contraction was established. This was repeated for a total of 60 steady-state myoelectric records from each subject. Each subject was then asked to produce several anisometric contractions types (e.g., flexion, extension, etc.). All contractions began with the subject's arm by the side in a comfortable neutral position. No constraints were placed on the force, velocity or range of the contraction except that the subject was asked to be consistent in reproducing the desired motion. Myoelectric data was acquired for 500 ms after the trigger. Each normally limbed subject repeated each specific contraction type a total of 60 times. The amputee was asked to repeat each contraction type 20 times.

The data for a subject and specific contraction type formed an ensemble of records. An ensemble average of the myoelectric signal was calculated by summing the sample values at an instant in time nT over all records. To remove measurement induced errors, each record is aligned with the sum using the crosscorrelation technique described by Woody [24] before it is added to the sum. The sum is then divided by the number of records in the ensemble to give an average value for the signal at that instant in time. This is done for each instantaneous time sample, (i.e., $n = 0, \cdots, 499$). The resulting average over many records will be approximately the mean value of the distribution of the instantaneous time samples. This procedure was used for averaging both the steady state signal and the signal from the anisometric contractions.

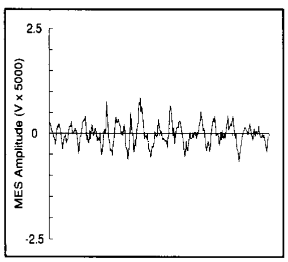
Results

All myoelectric control systems are based on the common assumption that the instantaneous value of the myoelectric signal contains no information. According to the accepted myoelectric signal generation models, the myoelectric signal measured using surface electrodes is stochastic [25]. This is due to the random nature of the pooled activity of the motor units within the pickup region of the electrodes. The firing intervals of single motor units are randomly distributed with a firing rate in the order of ten per second. As many motor units become active the firing rate increases and the pooled activity closely fits a Gaussian process. This implies that the instantaneous amplitude of the myoelectric signal is a random variable with zero mean. The myoelectric signal variance is a function of contraction level [26]. It is this relationship which is exploited in the conventional amplitude coded myoelectric control systems. The accepted signal generation model implies there is no information in the instantaneous value of the myoelectric signal.

Fig. 1(a) shows several 300 ms records of myoelectric signal from a normally limbed subject measured during a constant force isometric contraction. Although the electrode arrangement is unusual, the recordings are typical of myoelectric signal measured during a steady state isometric contraction. Fig. 1(b) is an ensemble average of 60 records of this steady state myoelectric signal. This figure illustrates that the steady state myoelectric signal is indeed zero mean and has no apparent structure. There is a factor 56 reduction



(a)



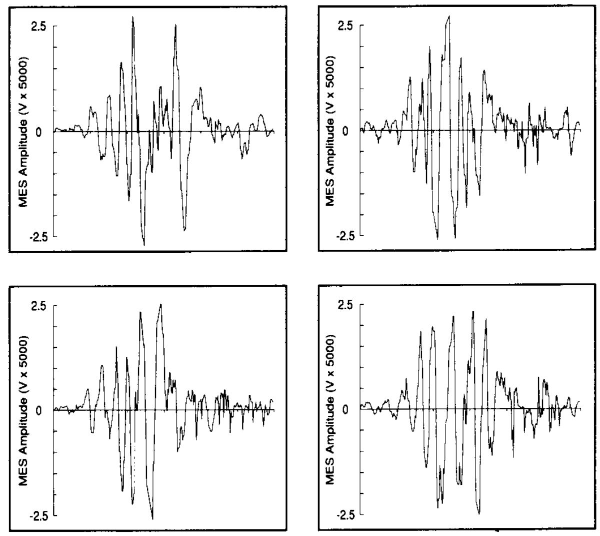
(b)

Fig. 1. (a) Four 300 ms records of steady state myoelectric signal (normally limbed subject). (b) The ensemble average of 60 records of steady state myoelectric signal. (Note: only the first 300 ms of the ensemble is shown.)

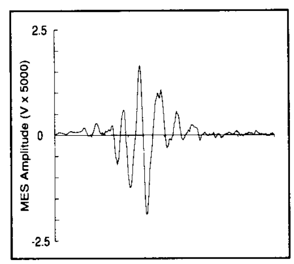
in the variance of the ensemble over the average variance of the individual waveforms in the ensemble. The reduction in variance agrees with that expected for an ensemble average of 60 random waveforms.

Although these results support the accepted myoelectric signal generation models, consider the waveforms shown in Fig. 2. This figure shows several records of the initial 300 ms of myoelectric signal measured from the same subject and electrode arrangement but taken during the initiation of elbow flexion. An ensemble average of 60 of these waveforms is shown in Fig. 2(b). This figure clearly shows that over 60 repeated trials there were many instantaneous samples which were not random but had predictable values which were maintained in the ensemble average waveform. The structure in this ensemble and its deterministic nature are apparent. The reduction in variance is only 7 rather than 60, which indicates there is a significant nonrandom component in these waveforms.

Similar structure can be found in myoelectric waveforms from other contraction types. Fig. 3 shows the dynamic pattens of myoelectric signal which accompany the onset of several different types of muscle contraction. These signals were again



(a)



(b)

Fig. 2. (a) Four 300 ms records of myoelectric signal acquired during the initial phase of elbow flexion (normally limbed subject). (b) The ensemble average of sixty 300 ms records of myoelectric signal acquired during elbow flexion. (Note: only the first 300 ms of the ensemble is shown.)

obtained from the same subject using the same electrode arrangement as described above. Each figure is the ensemble average of 60 waveforms recorded during the initial phase of a particular contraction, (i.e., elbow extension, wrist flexion, and humeral lateral/medial rotation). Although the reduction in variance (R) is large in some cases, it is still far less than that expected for an ensemble of random waveforms. The figures clearly illustrate that the inherent structure for each contraction type is reproducible. This deterministic component is of short duration and occurs during the initial phases of the contraction. It is interesting to observe that the structure in the waveform pattern for each contraction type is distinct. Results from the other normally limbed subjects were similar to those found from this subject. However, since the exact form and execution of the contraction types could vary between subjects, no attempt was made to compare data across subjects.

Fig. 4 shows the ensemble averages of 20 myoelectric waveforms acquired from the amputee subject. Each figure is the ensemble average of 20 waveforms recorded during the initial phase of a particular contraction, (i.e., extension, flexion, co-contraction, and humeral medial rotation). Although, as

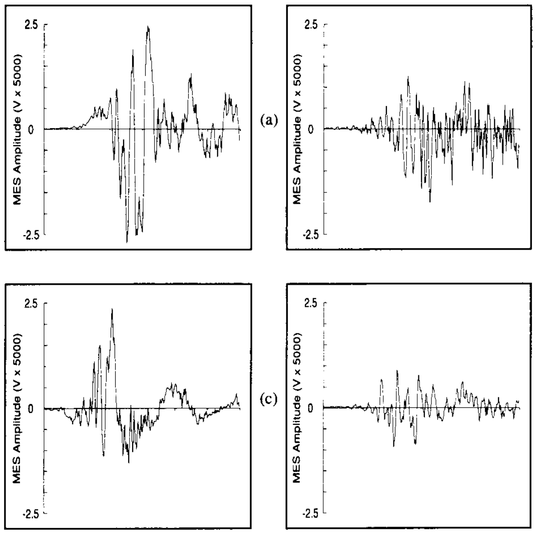


Fig. 3. The ensemble average of sixty 300 ms records of myoelectric signal acquired during each of four contraction types. (a) Forearm supination, $R = 12$; (b) elbow extension, $R = 30$; (c) wrist flexion, $R = 6.0$; and (d) forearm pronation, $R = 33$. (Note: R is the reduction in variance. Only the first 300 ms of each ensemble is shown. Data from a normally limbed subject.)

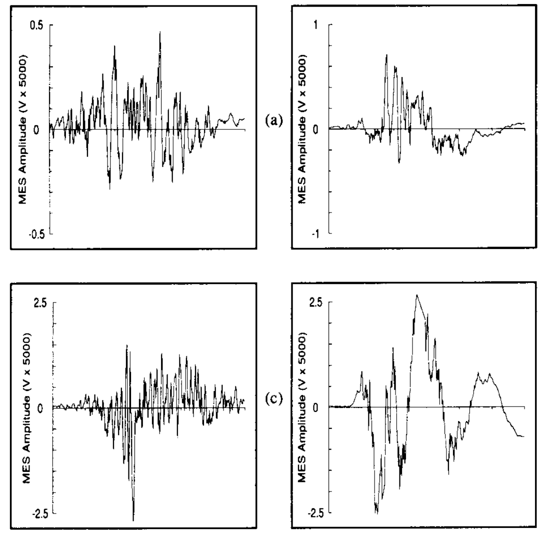


Fig. 4. The ensemble average of twenty 300 ms records of myoelectric signal acquired during each of 4 contraction types. (a) Inward humeral rotation, $R = 8.1$; (b) contraction of the flexor muscle group, $R = 4.1$; (c) contraction of the extensor muscle group, $R = 11.3$; and (d) biceps/triceps co-contraction, $R = 3.1$. (Note scale change in (a) and (b). R is the reduction in variance. Only the first 300 ms of each ensemble is shown. Data from an amputee subject.)

expected, the pattern of myoelectric activity is different than the normally limbed subject, the inherent structure in the signal from these contractions is again maintained.

Discussion

It is well known that the low frequency envelopes of myoelectric signals of intact muscles acting about a joint are different for different joint movements [27]. The change in the relative timing of on/off activity in the different muscles contributing to the contraction is reflected in the phasic envelopes of myoelectric activity measured during limb movement. In this case the pattern of the dynamic waveforms should change with different contraction types. This is certainly a factor in the observed patterns, but the deterministic structure in some of the waveforms implies more than just timing patterns of different muscle activations. Hannaford and Lehman [28] used short time Fourier analysis to investigate the activity patterns of the muscles which produce wrist and head movements. They calculated short time spectra (75 ms) from many overlapping time segments and combined them to form a spectragram for each motion. This is similar to the "voice print" analysis technique used in speech recognition. Their results showed that the myoelectric spectra measured during rapid movements of the wrist and head had less variability than those measured during isometric contractions. This is consistent with the low variability of the instantaneous myoelectric waveforms shown in this section.

An obvious mechanism which could produce this nonrandom component is movement artifact. However, attempts to reproduce these patterns by passive movement of the limb and rapid electrode lead motion have failed. The possibility that the determinisitic component is due to unknown sources of movement artifact such as the relative movement between signal sources and the detection electrodes has not been ruled out. Future work will investigate physiological and artifact based mechanisms which may produce these patterns. The emphasis of the present work is on the development of a myoelectric control system based on this new information.

Conclusions

The data presented in this section suggest there is considerable structure in the myoelectric signal during the onset of a contraction. Furthermore, this structure is distinct for contractions which produce different limb functions. Consequently, the actual structure of the myoelectric signal over time can be used to discriminate limb function. The result of this discrimination can be used to control the selection of a prosthetic limb function.

This is an entirely new concept. Other myoelectric control schemes have considered the signal when it has reached steady state conditions and have required signal averaging to obtain an accurate estimate of the contraction level. A control scheme based on signal dynamics would eliminate the delay associated with signal averaging and thus increase the time available for signal analysis. The approach is also attractive because these myoelectric patterns are generated by producing the contraction which naturally corresponds with the desired limb function. Such a natural scheme is preferred. As well, control schemes based on steady state levels or on the rate of increase in this level are limited to two limb functions, (three-states including off), for a single myoelectric channel. The number of functions which can be selected by the proposed scheme is limited only by the number of distinct patterns which can be generated. A further benefit is that proportional control of the selected function is easily incorporated into the new state selection scheme. Section II of this paper discusses the design, implementation, and evaluation of a multifunction myoelectric control system based on the classification of these patterns.

Section II. A New Multifunction Myoelectric Control System

Introduction

This section describes the development of a multifunction myoelectric control system based on the classifications of the myoelectric patterns discussed in Section I. The section will begin with a discussion on the selection of the pattern classifier. The features used to represent the myoelectric patterns are then introduced. The basic operation of the new multifunction myoelectric control system is described and several experiments are outlined to evaluate the control system performance. The section concludes with a discussion of the results and suggestions for future enhancements.

Classifier Selection

The pattern classifier is the major component of the new control scheme. There are several factors which must be considered when choosing a classifier for the present application. Due to the nature of the myoelectric signal, it is reasonable to expect a large variation in the value of a particular feature between individuals. This is particularly true in the case where muscle structure is altered due to an amputation or a congenital defect. Other factors such as changes in electrode position, myoelectric signal training, and body weight fluctuations will produce changes in feature values over time. A suitable classifier must be trainable to accommodate the expected individual differences and, as well, must be able to adapt to slow variations in feature values. Another factor arises from the user's perception of the myoelectric control system. The user must quickly feel confident in his ability to control the limb with reasonable accuracy. This limits the amount of time available to obtain the data which is needed to train the classifier. An artificial neural network (ANN) was chosen as the classifier for this application. This form of classifier determines the best set of feature weights based on a series of training patterns. The relative importance of each feature is determined during the training of the network. With a suitable training algorithm and sufficient training data the network automatically integrates the diverse feature set using a metric which minimizes the specified error, (i.e., mean squared error at the output). Recent work suggests that the relationship between input features for a specific class is retained in the stored weights of a trained network [29]. This means that structure within the feature set is used to enhance classification. In a way it is similar to a syntactic classifier which determines class assignment by feature/primitive structure. This is unlike nearest neighbor and discriminant classifiers which treat each feature as an independent element in the set. Section I illustrated that there is information in the time structure of the myoelectric signal. A classifier which uses this information would be appropriate. A neural network is also inherently a parallel structure in which the comparison to all classes is done simultaneously. The value of each output of the ANN is essentially a measure of the similarity of the unknown pattern to each of the classes.

The basic structure of the neural network used in the present study was a standard two-layer network in which all the input nodes, which correspond to the waveform features, are fully connected with the hidden layer. The hidden layer is in turn fully connected with the output nodes which correspond to pattern classes. The network is trained using a standard back propagation algorithm [30]. This algorithm was chosen due to its extensive use in the pattern recognition literature. Although the gradient descent nature of this algorithm means that learning can be slow, recent works by several groups [31]–[34] have discussed enhancements and alternatives to the standard backpropagation algorithm to improve network training and performance. Much time can be spent investigating alternative network structues and training algorithms. That exercise is beyond the scope of the present research.

Although the numbers of input and output neuronal units are determined by the number of features and classes, the optimum number of hidden units has not been established and appears to be problem dependent. The hidden layer should be kept as small as possible to reduce the complexity of the neural network algorithm and to improve generalization when using a small set of training data. However, the size must be sufficient to learn the necessary input/output mapping. The number of hidden units can influence the classifier performance in several ways. Increasing the number of hidden units will increase the time taken to do each error update in the backpropagation training and also will increase the time taken by the trained network to do the pattern classification. However, the number of iterations required for training may actually decrease because of the increased storage capability of the network, and thus training time may decrease. On the other hand, this increased network storage may allow the network to memorize the training data and make generalization to unknown patterns less successful. Too few hidden units will result in poor network performance because the network will be unable to learn the necessary input/output mapping represented in the training data. An optimum number of hidden units must be determined experimentally for this application.

Feature Selection

The success of any pattern classification system depends almost entirely on the choice of features used to represent the continuous time waveforms. Although the transient waveforms presented in Section I have a deterministic component, they also contain a random component. An attempt to classify these patterns using the sampled raw myoelectric signal will result in a classification accuracy which is unacceptable for control purposes. Much of the structural detail will be lost, however, if features are averaged over the entire transition period. A way of retaining some of this structural information is to segment the transient waveform and determine a set of features based on the statistics from each segment. This approach has been used to classify seismic activity [35], and biological waveforms such as the EKG [36] and carotid pulse waveforms [37].

Several factors will determine the best feature set but the most important are the computational complexity and class discrimination. The acceptable computational complexity is limited by the response time of the system which must be kept below 300 ms to reduce user perceived lag. Much of this time will be required to obtain enough signal samples to allow feature extraction. This leaves less than 100 ms to do the actual feature extraction and pattern classification. Features based on time statitics can be obtained within this time constraint using a simple hardware processor or a simple algorithm on a microprocessor. Features based on spectral parameters or AR models as discussed in the literature require much more complicated processing and were not considered. With this in mind the following features were chosen to represent the myoelectric patterns:

1) Mean Absolute Value —An estimate of the mean absolute value of the signal, $\overline{X}_i$, in segment i which is N samples in length is given by

$$\overline{X}_i = \frac{1}{N}\sum_{k=1}^{N}|x_k| \quad \text{for } i = 1, \cdots, I \tag{1}$$

where x_k is the kth sample in segment i and I is the total number of segments over the entire sampled signal.

2) Mean Absolute Value Slope —This is simply the difference between sums in adjacent segments, i and $i+1$, as defined by

$$\Delta\overline{X}_i = \overline{X}_{i+1} - \overline{X}_i \quad \text{for } i = 1, \cdots, I-1. \tag{2}$$

3) Zero Crossings —A simple frequency measure can be obtained by counting the number of times the waveform crosses zero. A threshold must be included in the zero crossing calculation to reduce the noise induced zero crossings. Assuming a system noise of 4 μV peak to peak and a system gain of 5000, this dead zone can be calculated to be ± 10 mV measured at the input to the A/D converter. Given two consecutive samples x_k and x_{k+1}, increment the zero crossing count, ZC, if

$$\begin{aligned} &x_k > 0 \quad \text{and} \quad x_{k+1} < 0, \quad \text{or} \quad x_k < 0 \\ &\quad \text{and} \quad x_{k+1} > 0, \quad \text{and} \quad |x_k - x_{k+1}| \geq 0.01\,\text{V}. \end{aligned} \tag{3}$$

This algorithm will fail to register a zero crossing if two consecutive samples of opposite sign fall within the deadzone. However, based on a uniform amplitude distribution, the probability of missing a zerocrossing is less than 0.2%.

4) Slope Sign Changes —A feature which may provide another measure of frequency content is the number of times the slope of the waveform changes sign. Once again a suitable threshold must be chosen to reduce noise induced slope sign changes.

Given three consecutive samples, x_{k-1}, x_k and x_{k+1}, the slope sign change count, SC, is incremented if

$$\begin{aligned} &x_k > x_{k-1} \quad \text{and} \quad x_k > x_{k+1}, \quad \text{or} \quad x_k < x_{k-1} \\ &\quad \text{and} \quad x_k < x_{k+1}, \quad \text{and} \quad |x_k - x_{k+1}| \geq 0.01\,\text{V} \\ &\quad \text{or} \quad |x_k - x_{k-1}| \geq 0.01\,\text{V}. \end{aligned} \tag{4}$$

5) Waveform Length —A feature which provides information on the waveform complexity in each segment is the waveform length. This is simply the cumulative length of the waveform over the time segment defined as

$$l_0 = \sum_{k-1}^{N}|\Delta x_k|. \tag{5}$$

where $\Delta x_k = x_k - x_{k-1}$ (difference in consecutive sample voltage values).

The resultant values gives a measure of waveform amplitude, frequency, and duration all within a single parameter.

These features are extracted from each time segment to create the total feature set used to represent the myoelectric pattern. The total number of features is determined by the number of time segments in the pattern. For deterministic patterns, increasing the number of time segments will increase the amount of class information available to the classifier. For patterns with a nondeterministic component, smaller time segments will result in a larger feature estimation error which will reduce system performance. It is obvious that the deterministic structure of the myoelectric patterns is more pronounced in certain contraction types. Other types present an almost random nature from the onset. Although the variance in the time structure of these signals is high, waveform statistics may be stable enough to allow pattern classification. Likewise, in the situation where the pattern structure is well defined but the duration is short, waveform features will provide extra information to the classifier. The effect of segment length on classification accuracy must be examined to determine a value which is the best compromise between class information and feature estimation error.

Control System Design

Although hidden layer size and segment length must be determined before the final control system structure can be defined, the basic system operation can now be established. Fig. 5 is a diagram of the neural network based myoelectric control system. The following is a brief description of the basic elements in the control system operation.

Segment Feature Extraction —The myoelectric signal is acquired using a single bipolar electrode pair and is amplified to an appropriate level by a standard myoelectric amplifier. The mean absolute value of the signal is monitored and when a threshold is exceeded, 200 samples (1 kHz sampling rate) are analysed to extract the pattern features. The feature set is then used as input to the neural network.

Network Training —During network training, the controller collects ten sample feature sets from each contraction type. This group of training feature sets is presented to the neural network with the corresponding class outputs. The backpropagation algorithm then adjusts the network weights from preset random values to reduce the output error to some specified value. The trained weights are stored and maintained until the system requires retraining.

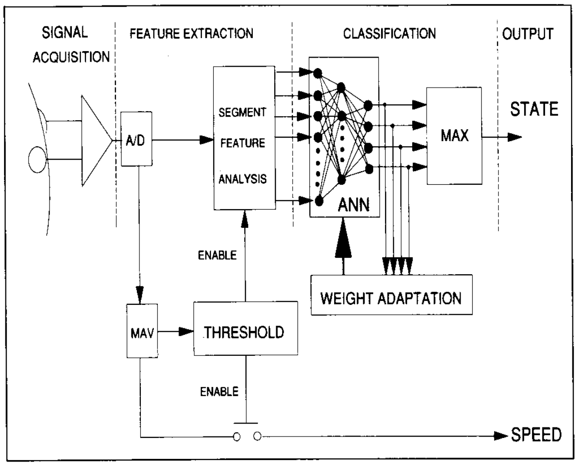


Fig. 5. Control system design.

Pattern Classification —During system operation, the feature is presented to the feedforward component of the network and the outputs of the network are scanned to choose the largest (MAX). If this is above a specified threshold, the prosthetic function corresponding to this output class is selected.

Proportional Speed Control —Once a function is selected, the system monitors the myoelectric signal to determine the level of activity. The speed of the function is then chosen based on this level. If the myoelectric signal drops below specified threshold for more that a specified length of time the function is terminated and the system adapts the network weights, initalizes buffers and counters and returns to its original state.

Weight Adaptation —The neutral network outputs are sent to the weight adaptation algorithm after each contraction is completed. The desired output is set to 0.9 if it was the largest network output, otherwise it is set to 0.1. The error between the actual network output and the desired output is used to update the network weights using the backpropagation procedure. In this way, the weights are being continually modified by the most recent patterns presented to the classifier. The learning rate for the backpropagation rule is kept small so that the long term trends in the generated patterns will produce the desired weight adaptation.

The new control scheme was implemented on a microcomputer (8 MHz Intel 80286) using Borland TurboC to simulate the control algorithm. The next section describes several experiments used to finalize the control system design and to evaluate the control system performance.

Control System Evaluation

Methods (General)

Several experiments were conducted to record myoelectric activity from the first 200 ms of repetitive muscle contractions to determine the effect of network structure and feature noise on the pattern classification accuracy of the new control strategy. A total of 18 subjects took part, however, not all subjects participated in all experiments. For the below elbow amputee subjects (SUB ID K-N) the electrodes were placed on the wrist flexor/extensor group. The above elbow amputees (SUB ID O-P) used the biceps/triceps electrode arrangement. Each amputee subject was asked to produce four different contractions which they felt they could reproduce reliably. The normally limbed subjects (SUB ID A-J, Q-R) were asked to produce four different limb functions: a contraction of the elbow flexor group; a contraction of the elbow extensor group; medial rotation of the humerus; and lateral rotation of the humerus. All contractions began with the relaxed arm by the side, the elbow fully extended and the wrist in a comfortable neutral position. It was left to the subject to establish the exact form of the contraction. This in part will determine the robustness of the new classification approach by testing it on the variable myoelectric patterns from many subjects. Typically 30 repeitions of each of the four contraction types were collected, although for some subjects less data was acquired and in some cases more. There was no subject training prior to the collection of data.

The data analysis program began by monitoring the signal with a 100 ms moving average window. When the moving average went above a specified threshold (typically 100 mV amplified MES), the feature selection began at a point 50 ms before the trigger point, (i.e., point 51 in the moving average window). From this point the data was analyzed in time segments from which the MAV, difference MAV, waveform length, slope sign changes and zero crossings were calculated. This was repeated for several successive segments providing a total feature set over the 200 ms frame. These features along with the five average statistics from the 200 ms frame were then used as inputs to the neural network. The data from each trial were divided into a training set and a test set. The training set was used to train the neural network classifier using a backpropagation algorithm. The test set was used to measure system performance. The training set/test set ratio, (#TR/#TST), was typically 1 : 1.

Experiment #1—Effect of Network Structure

Method —In this experiment the data from three subjects (2 normally limbed, 1 amputee) were used to investigate the effects of changing the number of hidden units and the size of the time segments on the classification accuracy to determine the optimum network structure. For each combination of the two variables, one half of the data set was used to train the network. The other half of the data set was used to evaluate classification accuracy of the trained network.

Results —The results from this investigation for one subject are shown in Fig. 6(a) and (b). Although there were differences in the effect of segment length and hidden unit number between subjects some clear trends did emerge. The error rate was initially high for all subjects when only 1 (200 ms) or 2 (100 ms) segments were used. The classification accuracy was highest at between 4–5 segments for all subjects. The error rate again increased if the number of segments was increased beyond 5 (40 ms). The effect of hidden unit number was less variable. A hidden layer with between 4–12 hidden

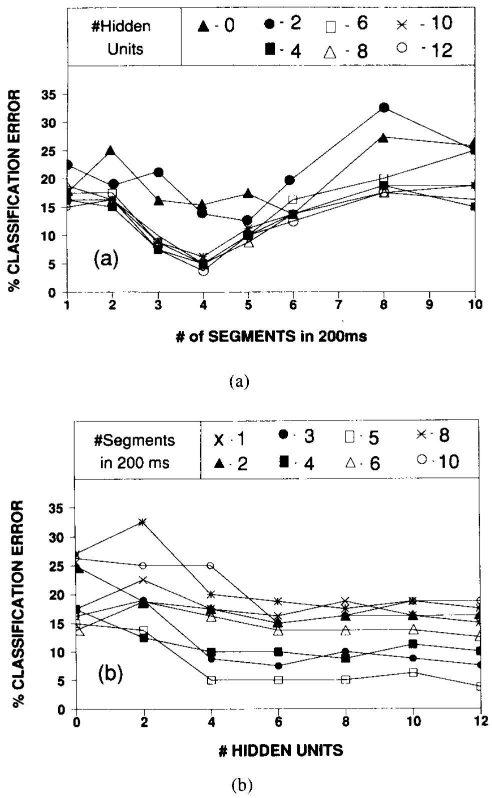


Fig. 6. Classification accuracy versus (a) segment length for several values of hidden unit number, (b) number of hidden units for several values of segment length. (Data from amputee subject K.)

units gave good classification accuracy for all three subjects.

Discussion —This analysis is lengthy, as it requires the training and testing of the neural network for many combinations of the variables. Network training time is excessive for many of the combinations and the network error often does not converge. It is not feasible to do this analysis for every subject nor is it reasonable to assume that it can be done for each individual user of this system. Values which perform well for the general user must be chosen. A network with eight hidden units trained on features from 5 time segments was found to train quickly and provided good classification performance for all subjects.

Experiment #2—Classification Results

Method —Data from 15 subjects were used to test the classification accuracy of the new control strategy using the network structure described above. The data from each subject was analyzed in five 40 ms time segments and the resulting 30 pattern features (25 segment features + 5 average features) were used as input to a two layer (30 inputs: 8 hidden: 4 outputs) neural network classifier.

Results —The results of this experiment are given in Table I. The correct classification (%CL) for the 9 normally limbed subjects averaged 91.2% (SD 5.6%) while the amputee subjects averaged 85.5% (SD 9.8%). Although the results

TABLE I
CLASSIFICATION RESULTS FOR FOUR CLASSES (CONTRACTION TYPES)

SUB ID	#TR SETS	#TST SETS	# ERRS	% CL
B	50	20	2	90
C	60	60	6	90
D	80	40	4	90
E	80	80	16	80
F	80	80	2	98
G	80	80	2	98
H	80	80	4	95
I	54	60	5	92
J	80	80	10	88
K	80	80	6	92
L	50	50	2	96
M	52	52	16	69
N	57	50	10	80
O	40	40	4	90
P	50	65	9	86

from the amputee subjects were comparatively less impressive, the difference between the two subjects groups was only statistically significant at the $p = 0.1$ significance level. These are excellent results considering that no subject training took place prior to data collection.

Discussion —There are several reasons for the larger variability in the amputee data. The amputees found it much more difficult to produce four distinct contraction classes. For the normally limbed subjects there was a noticeable amount of joint motion involved in the contractions. This of course cannot be duplicated by the amputees. The amputees also had less success in reproducing the contractions which they had chosen to represent the pattern classes. This can be attributed in part to disuse of the musculature in the stump. Most amputee subjects commented on this aspect. Although electrode placement was standardized for the normally limbed subjects (biceps/triceps), these locations could not be reproduced on the amputees. Electrode sites were chosen on the forearm musculature for below elbow amputees and on the upper arm for above elbow amputees, however no attempt was made to determine the optimum sites.

Experiment #3—Effect of Feature Noise

Method —Two tests were performed to determine the effect of feature noise on the classification accuracy and adaptation of a fully trained neural network classifier. Data sets from four subjects C, F, G, K) were used in these tests. Feature noise can be attributed to at least two sources. These are errors in feature values caused by the operator's inability to match the desired contraction pattern and errors due to the limited time available for feature estimation. It is difficult to quantify the feature estimation error. For deterministic patterns it will be zero but for patterns with a random component, such as those of the present study, it will be somewhat higher. Operator error is a major source of error in all myoelectric control systems. This error will be high initially and decrease as the operator becomes familiar with the control task. To maintain a high level of system performance the control system must be able to tolerate reasonable levels of feature noise. As well, the control system must be able to adapt to changes in operator patterns if performance becomes unacceptable.

The first test was performed to determine the level of feature noise at which the classifier performance becomes unacceptable. For this test, the complete data set for a subject was used to train the classifier. The same training set was then corrupted by adding uniformly distributed random noise to each of the features in the training set. The noise distribution was varied from ±5% to ±100% of the feature value. The trained network was then used to classify the corrupted training set for each value of feature noise.

The second test was performed to determine how quickly the network could be retrained if system performance becomes unacceptable. In such a situation training does not have to begin with random network weights but can continue from the previously determined values. In this way the control system may be retrained on the updated patterns more quickly. For this test the uncorrupted training data was used to train the network until the average pattern output error (defined as the average error between the desired output and the actual output for each pattern during a training cycle) was less than 0.05. The training time taken to reach this stopping criteria was recorded. At that point the data set was corrupted with noise which was uniformly distributed over ±5% of the feature value. The network was retrained with the corrupted data under the same stopping rule and the time taken for retraining was recorded. The process was repeated for other percentage noise values.

Results —The results of the first test for the four subjects are shown in Fig. 7(a). For all subjects, there is little degradation in classification accuracy for low to moderate levels of feature noise. The error rate is below 5% for up to ±15% feature noise for all subjects. A 95% classification accuracy is maintained for two of the four subjects up to ±25% feature noise. This noise immunity is essential for the present application in which the pattern generator is a human operator. The variability in the features will be a function of the individuals' ability to reproduce the desired pattern. It is obvious, however, that as the level of feature noise increases, the number of classification errors becomes unacceptable. In this case the system must be retrained on new control patterns.

The results of the second test for one subject are shown in Fig. 7(b) which plots the average output error in the training patterns as a function of training time. The training time has been normalized by the training time required for the uncorrupted data. The results show that the network was able to adapt quickly to abrupt changes in feature values of up to ±25%. Beyond this point training time became excessive or the network was unable to converge to the desired output error. Similar results were found for the other subjects.

Discussion —Any state selection error in a myoelectric control system is unacceptable to the user. Realistically, however, most systems are designed with a specification of less than 5% error. The largest component of the control system error is the operator error which usually exceeds 5% initially but is reduced with operator training. It is reasonable to expect that once the operator is familiar with the control system,

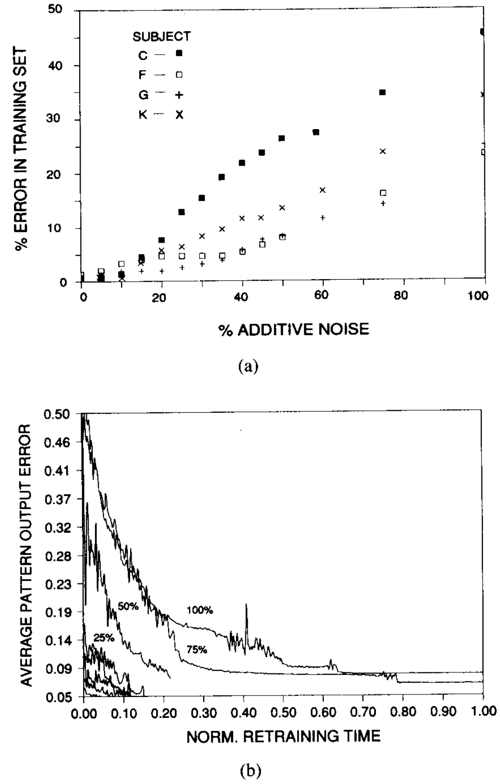


Fig. 7. (a) Effect of feature noise on classification accuracy for four subjects. (b) Network adapting to feature noise. (Data from amputee subject K.)

feature noise due to operator error and feature estimation will be less than 10%. Fig. 7(a) demonstrates that the control performance is within the acceptable range for this level of feature noise. There are, however, other factors which can alter the control patterns. It has been shown there is a substantial change in the myoelectric signal with motor skill practice [38]. It is reasonable to assume that a similar change will occur in the signals of first time users of myoelectrically controlled artificial limbs. These changes can occur because of modifications to the muscle recruitment patterns and because of an increased familiarity with the required control task. It is expected that these changes will cause slow varying changes in the myoelectric patterns used in the new control system. Feature changes due to these mechanisms may be sufficient to cause unacceptable system performance. It is necessary then, to have a classifier which can adapt to these changes to maintain performance. As shown in Fig. 7(b), a neural network has this ability. This adaptation can be done in two ways. The system can be retrained with a new set of training data or the system can be continually adapting under the assumption that an accurate classification has been made.

Experiment #4—Electrode Position Sensitivity

Methods —This experiment was undertaken to investigate the effect of electrode position errors on the system performance. Such variations are expected due to socket/stump

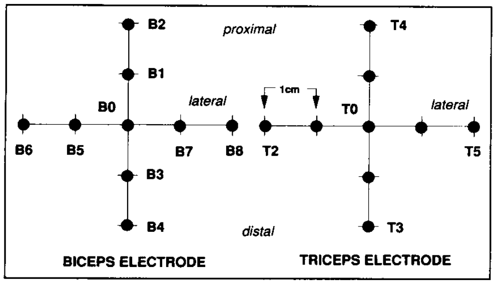


Fig. 8. Definition of electrode positions for electrode displacement test (viewed from the front).

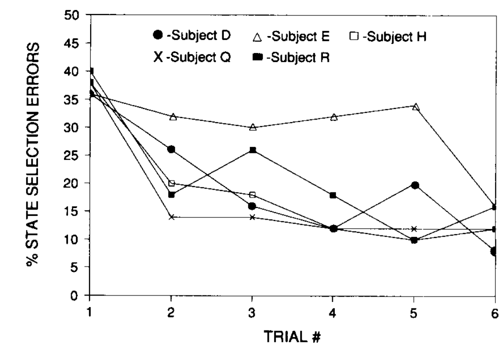


Fig. 9. State selection accuracy.

misalignment. Data from four contraction types were collected from a base electrode site (see position B0T0 in Fig. 8), from two normally limbed subjects. This data was used to train the control system. The biceps electrode was then displaced by 1 and 2 cm as shown in Fig. 8 (positions B1-B8). The triceps electrode was then displaced (positions T2-T5). As well, worse case conditions were tested with the biceps electrode at B4 and the triceps electrode at T4, and then with the biceps electrode at B6 and the triceps electrode at T5. Control data were collected from the base position (position B0T0) at the beginning and end of the experiment.

Results —Table II gives the results of this investigation. The results from Subject A show only a slight decrease in the classification performance for displacements of either electrode. The 5% decreases at positions B2T0, B0T2, and B6T5 are countered by 5% increases at several other displacements and there is no pattern to the errors. The data from Subject D also show a lack of sensitivity to displacements of the biceps electrode and of medial/laterial displacements of the triceps electrode. In most cases the difference in classification error is close to the expected experimental error (2%). There is, however, a significant increase in classification errors for this subject when the triceps electrode is longitudinally displaced. The pretest and post test controls agree within experimental error for Subject D. The difference between these controls for Subject A, however, is greater than expected. This suggests that the variability in classifier performance for this subject is most likely due to operator error and not feature variations caused by electrode displacement.

TABLE II
ELECTRODE DISPLACEMENT POSITION AND CLASSIFICATION. CLASSIFIER TRAINED WITH 30 SETS FROM EACH OF FOUR CONTRACTION TYPES. ALL TEST USE TEN SETS FROM FOUR CONTRACTION TYPES (* DENOTES PRESTEST AND POST TEST CONTROL DATA)

	SUBJECT A		SUBJECT D	
Pos.	Errs	%Cl.	Errs	%Cl.
*B0T0	3	92.5	2	95.0
B1T0	2	95.0	—	—
B2T0	5	87.5	4	90.0
B3T0	1	97.5	—	—
B4T0	3	92.5	3	92.5
B5T0	3	92.5	—	—
B6T0	3	92.5	1	97.5
B7T0	3	92.5	—	—
B8T0	3	92.5	3	92.5
B0T2	5	87.5	1	97.5
B0T3	2	95.0	6	85.0
B0T4	1	97.5	7	82.5
B0T5	4	90.0	2	95.0
B4T4	1	97.5	4	90.0
B6T5	5	87.5	8	80.0
* B0T0	0	100.0	3	92.5

Discussion —The 2 cm displacement used in the present test is far larger than any displacement which would occur in a well designed socket. Clinical experience has shown that electrode displacements of > 1 cm are unusual. The test results do show that over all, the classification system is insensitive to small changes in electrode position. This lack of sensivity suggests that the widely spaced electrode configuration is detecting a signal which represents the global activity within the limb. This is unlike the typical closely spaced bipolar pair which detects a signal from a small region of muscle directly below the electrodes. Although such electrodes are ideal for commercially available myoelectric control systems where crosstalk is considered noise, in our system it is the crosstalk which is producing the unique myoelectric pattern used for classification. The lack of electrode position sensitivity also demonstrates one advantage of the neural network classifier—its ability to generalize from a few training patterns. Although the value on the neural network output for the desired class may be lower for the displaced signals, the classification is still correct.

Experiment #5—State Tracking

Methods —Five normally limbed subjects took part in this experiment to test the accuracy of tracking a random state target. The equipment setup and electrode locations were the same as in experiments 1–3. Each subject was asked to produce ten repetitions of the four contraction types. The feature set was extracted from the myoelectric patterns associated with these contractions. These 40 features sets were used to train the neural network classifier. After the network had been trained, the subjects were asked to duplicate a series of states presented to them on a computer screen. The states were presented in a pseudo random order and were of the form UP, DOWN, OUT, and IN. These states corresponded to the myoelectric patterns from elbow flexion, elbow extension, outward humeral rotation and inward humeral rotation respectively. A total of 300 state targets was presented to each subject. These 300 targets were divided into six trials with each trial consisting of 50 targets. Rest periods were given between trials to avoid fatigue. The task was not timed, so a new target was not presented until the subject responded to the previous target. The target state and classifier response were used to adapt the network weights over the duration of the test. The number of errors in each trial was recorded to determine the effect of training on the classification accuracy.

Results —The results of this test are shown in Fig. 8. Initial classification errors were very high, ($> 35\%$), for all subjects. However, four of the five subjects displayed a rapid decrease in classification error over the 6 trials, confirming that the task was easily learned. The fifth subject (E) achieved approximately the same classification error, (15%), for trial 6, but had difficulty throughout the test. The reason for this problem was in the choice of the initial patterns. This highlights the main limitation of the new approach. The initial patterns which are chosen to represent state function and are used to train the classifier must be distinct. It is difficult to determine a meaningful estimate of how distinct each pattern is from the patterns of other classes. Although the pattern differences can be calculated using some form of distance measure on the feature sets, it may not be indicative of the class differences after the nonlinear transformation of the feature set by the neural network.

The experiment described above measures only the state selection component of the new control system. The proportional control of the function is achieved by continuing to monitor the MAV of the myoelectric signal after the state has been selected. This value is used as an estimate of the desired speed of the limb function.

Fig. 10 illustrates a typical example from the integration of the state selection scheme with proportional control during the normal operation of the new control scheme. Fig. 10(a) is a section of raw myoelectric signal which resulted in the selection of State 2 at time T_1 as shown in Fig. 10(c). The time T_d was the time delay between the time the MAV exceeded the Von threshold until the time the state was selected. This state selection delay is typically in the order of 225 ms. To avoid a rapid "turn on" transient, the proportional output signal is buffered by a 100 ms moving average window which has been initially reset to zero. This introduces a ramp in the proportional signal after which time the speed of the device is proportional to the MAV as shown in Fig. 10(d). The figure shows that the state remained high until the MAV, shown in Fig. 10(b), fell below a threshold Voff. After this time another myoelectric pattern was generated by the user and classified by the control system. This resulted in another state selection at time T_2.

Discussion

The results of this method of myoelectric control are very encouraging. It was demonstrated that the neural network classifier could accomodate the diverse set of the myoelectric patterns produced by intact and amputated musculature. The subjects were not required to reproduce contractions with a specific force, velocity or duration but contracted in a way which was both comfortable and reproducible. During training of the neural network, the classifier was able to adapt to each subject's distinct myoelectric patterns. The pattern classification system could correctly classify between 70–98% of the test patterns presented after an initial training of the neural network. It was noted that this performance was achieved with no training of the user.

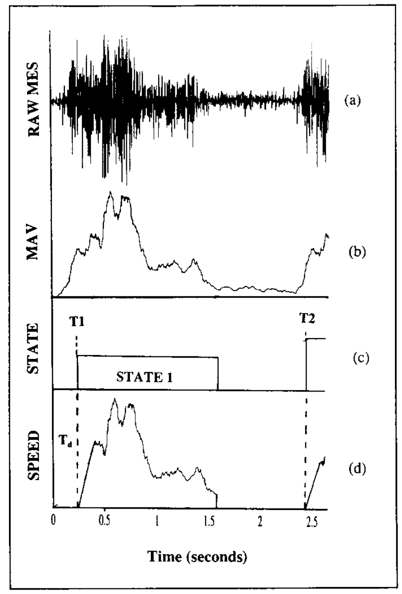


Fig. 10. (a) Raw myoelectric signal, (b) output of 100 ms MA window (c) control system output-state (d) control-system output-speed. (Arbitrary units for vertical scale.)

These tests confirmed that the performance of the neural network based classifier will be unaffected by small variations in feature values. The results also suggest that the network could continually adapt to changes in the pattern class features. In a way, the abrupt changes shown in Fig. 7(b) are worst case conditions of this feature drift. It is reasonable to assume that the most common feature value variation will be a slowly varying trend rather than an abrupt change. In this case the output errors can be used to continually update the network weights to compensate for these trends. This is particularly useful for subject training during which time the user will become more proficient at using the control system. If the network is allowed to adapt to these training patterns it will also become more capable of recognizing the user patterns. This will allow the user to adopt an approach to generating the desired pattern classes which is comfortable and efficient rather than forcing the user to continue to use the same strategy which was used when the task was unfamiliar.

Acquisition of the set of test patterns, which consists of several exemplar patterns from each of the contraction classes, requires the generation of about 40 separate contractions by the user. The time required to train the control system on the test patterns is typically less than 5 min for the microcomputer implementation. This is about 100 presentations of the set of test patterns to the neural network. The network training time is device dependent and will be less for a faster processor. This makes occasional retraining of the control system feasible. The time required to extract the feature set from the 200 ms of sampled data is approximately 10 ms. The feedforward calculation of the neural network classifier requires about 10 ms. These values are again device dependent. The overall state selection delay is less than 250 ms. This results in no user perceived delay. The weight updates take approximately 20 ms after the function has stopped. A delay of 200 ms is also added during this time to ensure that the myoelectric activity has returned to its resting value before the system is rearmed.

Amputee and normally limbed subjects have used the microcomputer-based system to realize proportional control of a bench mounted electric elbow and hand prosthesis. Good performance was achieved by most subjects. Implementation of this scheme on a dedicated microprocessor (TI TMS320C25) to be used for clinical trials is now in progress.

CONCLUSION

This paper has introduced the observation that the myoelectric signal is not random during the initial phase of muscle contraction. The information found in the signal structure during this phase provides a means of classifying patterns from different contraction types. This information is used as the basis of a new multifunction myoelectric control system. The new control scheme increases the number of functions which can be controlled by a single channel of myoelectric signal but does so in a way which does not increase the effort required by the amputee. The control signals are derived from natural contraction patterns which can be produced reliably with little subject training.

It was also demonstrated that the new multifunction control strategy can be implemented using an artificial neural network to classify myoelectric patterns. The ability of the network to learn the feature values which represent the pattern classes provide a means of tailoring the control system to the individual. A control system based on a neural network classifier provides the user with a means of retraining the control system to maintain a high degree of accuracy in the system's performance. The system performance is also enhanced by the ability of the network to adapt to moderate changes in the control patterns.

Although the control scheme development was based on the observation that there is deterministic structure in the instantaneous value of the myoelectric signal, it does not require this. It will utilize whatever form of information may be available, whether it be in the frequency, amplitude or envelope of the signal. Many of the features used in the present study are highly correlated. Work is continuing to determine if a subset of these features can give similar performance. Likewise, features extracted from more than one myoelectric channel may enhance system performance. Further work is also necessary to define an appropriate training procedure for the operator of this system. Much research is necessary to determine the potential of this control scheme.

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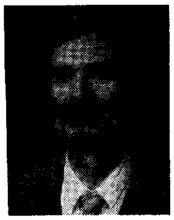
Bernard Hudgins received the B.Sc., M.Sc., and Ph.d. degrees from the Department of Electrical Engineering, University of New Brunswick in 1978, 1980, and 1990, respectively.

He is currently a project engineer at the Institute of Biomedical Engineering and an Adjunct Professor in the Department of Electrical Engineering at UNB. His main research interests are in myoelectric control and other areas of biological signal processing.

Dr. Hudgins is a Registered Professional Engineer and a member of the Canadian Medical and Biological Engineering Society.



Philip A. Parker (S'70–M'73–SM'86) received the B.Sc. degree in electrical engineering from the University of New Brunswick in 1964, the M.Sc. degree from St. Andrews, Scotland, in 1966, and the Ph.D. degree from the University of New Brunswick in 1975.

He is currently Professor of Electrical Engineering at the University of New Brunswick and a research consultant to the Institute of Biomedical Engineering at UNB. His main research interests are in the areas of biological signal processing.

Dr. Parker is a member of the Canadian Medical & Biological Engineering Society and of the International Society of Electrophysiological Kinesiology.

Robert N. Scott (M'78–SM'86) received the B.Sc. degree in Electrical Engineering from the University of New Brunswick in 1955 and the honorary D.Sc. from Acadia University in 1981.

Since 1956, he has been a member of the faculty of the Department of Electrical Engineering, University of New Brunswick, where he has held the rank of Professor since 1970. He initiated biomedical engineering research at UNB and was the Director of the Institute of Biomedical Engineering there from 1965 until his retirement in 1990. His research interests center around the clinical application of biological signal processing.

Dr. Scott is a Fellow of the Canadian Medical and Biological Engineering Society, a founding member of the Rehabilitation Engineering Society of North America, and a member of the International Society of Electrophysiological Kinesiology. He is a Registered Professional Engineer and a Certified Clinical Engineer.