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AN ADAPTIVE MULTIFUNCTION MYOELECTRIC CONTROL SYSTEM

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1 INTRODUCTION

Myoelectric systems have received widespread use as controls of prosthetic devices for individuals with amputations or congenitally deficient upper limbs, (Parker and Scott, 1988). Many systems are now available commercially to control a single device (hand, elbow, wrist). These systems extract a control signal based on an estimate of the amplitude, (Dorcas and Scott, 1966), or on the rate of change, (Childress, 1969), 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 1 of 3 states of device operation, or it is derived from 2 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, or it may be controlled in a manner proportional to the level of myoelectric activity. 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, (Scott and Parker, 1988). 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 multi-channel 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, (Vodovnik *et al.*, 1967). An attempt to increase the number of states per channel by using state feedback has been unsuccessful, (Richard *et al.*, 1983). Philipson (1985) has suggested an extension of the rate sensitive approach from 3 to 9 states by using two myoelectric channels and although results on non-amputee subjects were promising (Philipson and Sörbye, 1987; Sörbye and Philipson, 1987), no further development has been reported. The Boston elbow, (Williams, 1990) and Utah Arm, (Jacobson *et al.*, 1982) 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. Other multifunction prostheses have been developed using several channels of amplitude coding, (Schmidl, 1977). These require the existence of several electrode sites which are usually difficult if not impossible to locate on high level amputees. 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, (Condo, 1983). The reason for this lengthy training period is that muscles seldom contract independently. The natural way of activating muscle is within a complex pattern in which many muscles are recruited to produce not only the desired movement, but as well, to stabilize joints and provide resistance, (Wirta *et al.*, 1978). To isolate these muscles requires much concentration. The objective in the design of any prosthetic control system must be to allow the amputee to concentrate on things other than the contraction of specific muscles; the control is then done on a subconscious level, increasing the degree of acceptance of the prosthesis and the efficiency of its use, (Doubler and Childress, 1986).

The Institute of BioMedical Engineering at UNB, along with Hugh Steeper Limited and the Liberty Mutual Research Center have been undertaking a collaborative research effort to determine a new way of controlling a multifunction prosthetic limb from a single channel of myoelectric data. Other single channel multifunction myoelectric control systems (Graupe, 1978) have been inadequate for this task because of the limited amount of information which was used in the classification of the myoelectric patterns or because of the lack of adaptability of the control system. The present collaborative research project has resulted in a new 5-state myoelectric control system which uses the information found in the first 200 ms of myoelectric signal following the initiation of a contraction to determine the function state. This state selection scheme is easily integrated with proportional control to provide the required speed control of the selected function. The next section provides a brief description of this new control system.

2 A NEW APPROACH TO MULTIFUNCTION CONTROL

2.1 *Control Signal*

All myoelectric controls systems have been designed under the assumption that no information is available in the instantaneous value of the myoelectric signal. According to the accepted myoelectric signal generation models, the myoelectric signal measured using surface electrodes is stochastic, (DeLuca, 1979). 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 Gaussian variable with zero mean. The myoelectric signal variance is a function of contraction level, (Parker, 1975). 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. Confirmation of this theory is given by Figure 1a. This is an ensemble average of 60 records of steady state myoelectric signal obtained from a normal subject using a single bipolar electrode pair with one active electrode placed on the biceps brachii and the other on the triceps brachii. It illustrates that the steady state myoelectric signal is indeed zero mean and has no apparent structure. There is a factor of 56 reduction in variance of the ensemble average waveform 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.

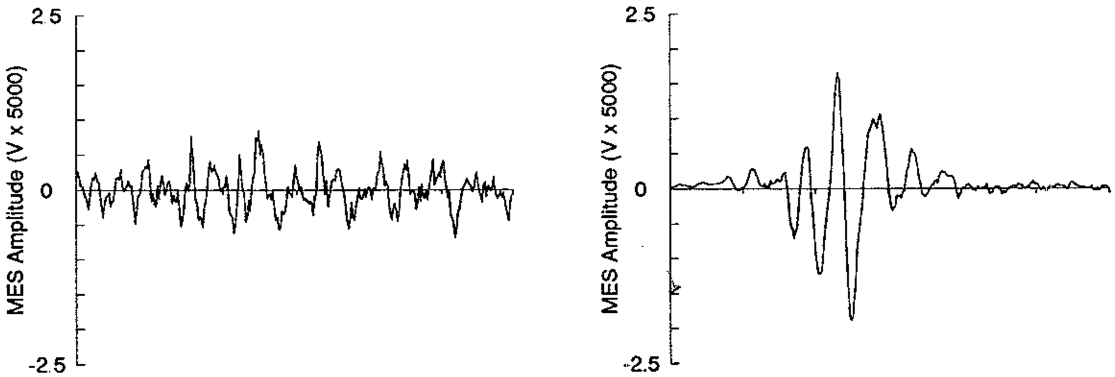

Figure 1 The ensemble average of sixty 300ms records of myoelectric signal (a) steady state (b) initiation of elbow flexion.

Recent work, however, has demonstrated that the instantaneous value of the myoelectric signal measured during the initiation of a contraction is not random but contains deterministic structure, (Hudgins, 1991). As an example, consider the waveform shown in Figure 1b. This shows the ensemble average of 60 records of myoelectric signal measured from the same electrode arrangement but taken during the initiation of elbow flexion. This figure demonstrates that much structure is maintained in the ensemble suggesting that the myoelectric signal patterns of the ensemble records are reproducible and deterministic. The reduction in variance is only 6.9 rather than 60, which indicates there is a nonrandom component in these transient waveforms. Similar structure has been found in myoelectric waveforms from other contraction types and in signals recorded from amputee musculature. This deterministic component is of short duration and occurs during the initial phase of the contraction. It has also been observed that the structure in the waveform pattern for each contraction type is distinct, (Hudgins, 1991). In this case 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. Once selected, the speed of the function can be controlled in a manner proportional to the strength of the contraction.

2.2 *Control System Design*

A new 5-state myoelectric control system has been implemented using this classification and control strategy. The control system uses a neural network classifier to determine the control system state from the user generated myoelectric patterns. The control signals are derived from natural contraction patterns which can be produced reliably with little subject training. Figure 2 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.

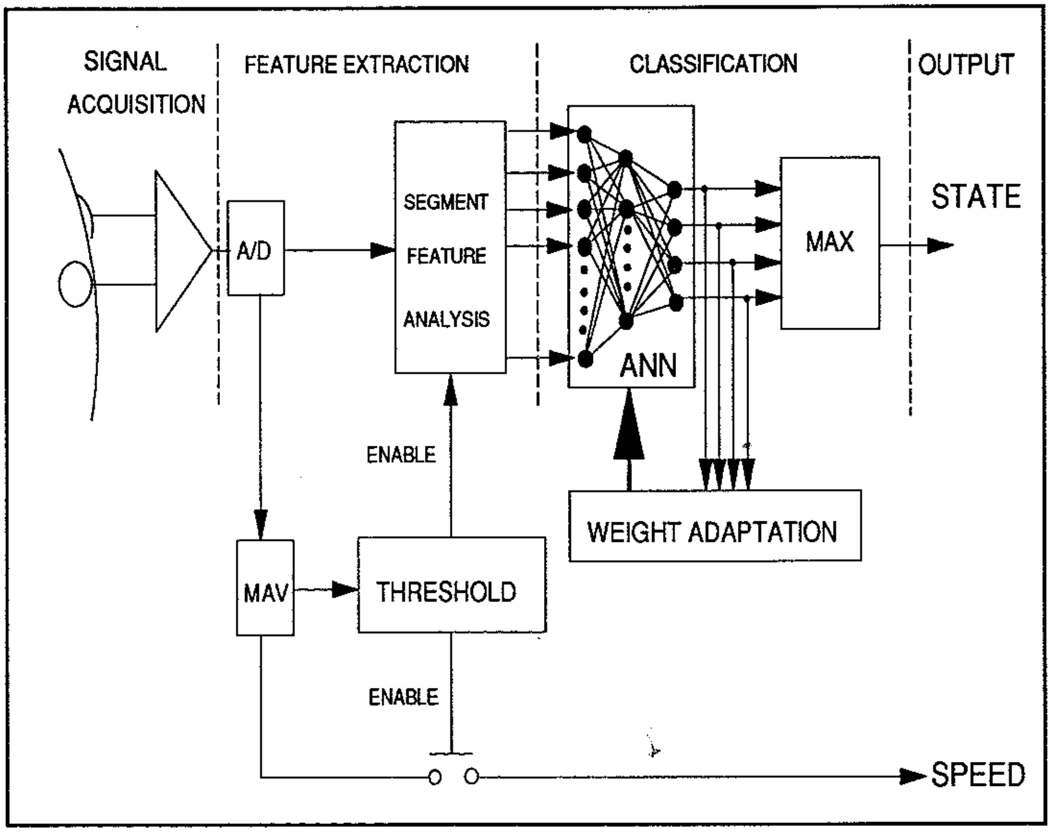

Figure 2. Control System design.

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 (1KHz sampling rate) of myoelectric data are stored. The myoelectric data is divided into several time segments to preserve pattern structure and features are extracted from each segment. Several factors determine the best feature set used to represent the continuous time waveforms 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 milliseconds 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 milliseconds to do the actual feature extraction and pattern classification. With this in mind the following features were chosen to represent the myoelectric patterns:

- the mean absolute value of the signal in several consecutive time segments and the difference in MAV of adjacent time segments were used to represent the time structure in the waveform;
- the number of zero crossings, the number of slope changes, (turns), and the waveform length in several consecutive time segments were chosen to represent waveform complexity;
- and finally the mean value of each of the features over all time segments was chosen to complete the feature set.

Network Training—The feature set is then used as input to the neural network. The basic structure of the ANN used 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 was in turn fully connected with the output layer nodes which correspond to pattern classes. The network was trained using a standard backpropagation algorithm adapted from Pao (1988). During network training, the controller collects 10 sample feature sets from each contraction types. 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.

Pattern Classification—During system operation, the feature set 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 a specified threshold for more that a specified length of time the function is terminated and the system adapts the network weights, initializes buffers and counters and returns to its original state.

Weight Adaptation—The neural 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 no one pattern can greatly change the network weights. The long term trends in the generated patterns will produce the desired weight adaptation.

2.3 *Control System Evaluation*

A laboratory based implementation has been evaluated to determine the potential of this form of myoelectric control. Nine normally limbed subjects and 6 amputees (2 above elbow and 4 below elbow) took part in these tests. One electrode from a bipolar electrode pair was placed on each of the biceps brachii and triceps brachii for the normally limbed and above elbow amputee subjects. The below elbow amputee subjects used an electrode arrangement on the wrist flexor/extensor group. Each subject was asked to repetitively produce 4 different limb functions during which the myoelectric signal was sampled. For the normally limbed subjects these corresponded to a contraction of the elbow flexor group, a contraction of the elbow extensor group, and medial and lateral rotation of the arm. The amputees chose contractions which they felt they could reproduce reliably. The subjects were not required to produce 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 adapt to each subject's distinct myoelectric patterns.

Various network structures were tested to determine the best configuration for this application. Although the results were subject dependent, a 2-layer network with 30 inputs (corresponding to features from five 40ms time segments), 8 hidden neurons and 4 output neurons (corresponding to the 4 active state classes) performed well for all subjects. This design yielded average classification rates of 91.2±5.6% and 85.5±9.8% for the normally limbed and amputee subjects respectively. This performance was achieved with no training of the user. Other tests demonstrated the insensitivity of the control system to errors in electrode positioning and feature noise.

A tracking study, in which 5 normally limbed subjects generated control system states to match a random presentation of computer generated target states, demonstrated that the control task was easily learned. State selection accuracy rose quickly from an initial level of approximately 60% to between 85-95% for all subjects after the presentation of only 300 targets (approximately 1/2 hour total subject training time). The integration of state selection with proportional speed control has also been demonstrated.

For microcomputer implementation, (8 MHz Intel 80286), the time required to train the control system on the test patterns is typically less than 5 minutes, (about 100 test set presentations to the neural network). 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 feedfoward calculation of the neural network classifier requires about 10 ms. This results in an overall state selection delay of 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. A moving average window size of 100 ms provides good system response while maintaining an adequate estimate of the MAV for proportional speed control.

2.4 *Discussion*

The results of this method of myoelectric control are very encouraging. It has been demonstrated that the neural network classifier can accommodate the diverse set of myoelectric patterns produced by intact and amputated musculature. 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. 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.

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 structure, frequency, amplitude or envelope of the signal. The ability of the network to learn the feature values which represent the pattern classes provides 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 control system to adapt to moderate changes in the control patterns. This is particularly useful for subject training during which time the user will become more proficient at using the control system. If the control system 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.

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.

3 CONCLUSIONS

Since the earliest single function myoelectric control systems became available for clinical use in the early '60's, the challenge of providing an effective control system for multifunction prostheses has frustrated designers. Many attemps have been made, and limited laboratory success reported, but clinical success has been limited at best. We are hopeful that the new technique described above will form the basis for multifunction control systems of clinical value. The challenge of providing simultaneous independent control of several degrees-of-freedom will remain, to provide an opportunity for future generations of researchers.

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