A Robust, Real-Time Control Scheme for Multifunction Myoelectric Control

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***Abstract*—This paper represents an ongoing investigation of dexterous and natural control of upper extremity prostheses using the myoelectric signal (MES). The scheme described within uses pattern recognition to process four channels of MES, with the task of discriminating multiple classes of limb movement. The method does not require segmentation of the MES data, allowing a continuous stream of class decisions to be delivered to a prosthetic device. It is shown in this paper that, by exploiting the processing power inherent in current computing systems, substantial gains in classifier accuracy and response time are possible. Other important characteristics for prosthetic control systems are met as well. Due to the fact that the classifier learns the muscle activation patterns for each desired class for each individual, a natural control actuation results. The continuous decision stream allows complex sequences of manipulation involving multiple joints to be performed without interruption. Finally, minimal storage capacity is required, which is an important factor in embedded control systems.**

***Index Terms*—Classification, embedded system, EMG, myoelectric, pattern recognition, prostheses.**

I. Introduction

THE surface myoelectric signal (MES) is an effective and important system input for the control of powered prostheses. This control approach, referred to as myoelectric control, has found widespread use for individuals with amputations or congenitally deficient upper limbs. Clinical evaluations of myoelectrically controlled prostheses indicate that the three major factors that determine the acceptance rates by the users are: the type of prosthesis, the degree of user training, and the control strategy. It is the third factor that we consider here. It has been observed [1] that low acceptance rates result when the user perceives an inadequate controllability—specifically a lack of intuitive and dexterous control. A myoelectric control system is described that offers exceptional performance with regard to three important aspects of controllability: the accuracy of movement selection, the intuitiveness of actuating control, and the response time of the control system.

- *Accuracy* is essential to faithful realization of a user's intent. Accuracy must be as high as possible, although it is difficult to define the threshold of acceptability, as no definitive clinical trials have addressed this issue.
- *An intuitive interface* to the control system relieves the mental burden of the user. In this regard, a control system should be capable of "learning" the muscle activation patterns chosen as the most "natural" by an individual to actuate motion.
- *The response time* of a control system should not introduce a delay that is perceivable by the user. This threshold is generally regarded to be roughly 300 ms. This places a real-time constraint on the control system's tasks of acquiring and processing myoelectric data.

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II. Background

The concept of myoelectric control was introduced in the 1940s [2]; however, the technology of the day was not adequate to make the clinical application viable. It was with the development of semiconductor device technology, and the associated decrease in device size and power requirements that clinical application saw promise, and research and development increased dramatically. Significant progress was made internationally in the 1960s [3]–[8], but it was in the 1970s that myoelectric prostheses began to make a significant clinical impact. Powered prostheses with myoelectric controllers were routinely fitted to upper limb deficient clients, and clinical evaluations of the functional benefits carried out [9].

Electrically powered prostheses with myoelectric control have several advantages over other types of prostheses: the user is freed of straps and harnesses required of body powered and mechanical switch control; the MES is noninvasively detected on the surface of the skin; the controller can be adapted to proportional control with relative ease; and muscle activity required to provide control signals is relatively small and can resemble the effort required of an intact limb.

Many myoelectric control systems are currently available that are capable of controlling a single device in a prosthetic limb, such as a hand, an elbow, or a wrist. These systems extract control information from the MES based on an estimate of the amplitude [10] or the rate of change [11] of the MES. Although these systems have been very successful, they do not provide sufficient information to reliably control more than one function (or device) [12]; the extension to controlling multiple functions is a much more difficult problem. Unfortunately, these are the requirements of those with high-level (above the elbow) limb deficiencies, and these are the individuals who could stand to benefit most from a functional replacement of their absent limbs.

If one is to increase the number of devices under the control of the MES, it is clear that a more sophisticated means of discriminating different muscle states is needed. Two things are needed for this to be possible.

1) *More information must be extracted from the MES about the active muscle state*. The manner in which one might extract more information from the MES could involve one or both of the following approaches.
   - Use multiple channels of MES, providing localized information at a number of muscles sites.
   - Develop a *feature set* that extracts as much information as possible from the MES that serves to discriminate different classes of movement.
2) *A classifier, capable of exploiting this information, must be constructed*. The role of the classifier is to assimilate and exploit the information it receives, and decide from which class the information originates.

These criteria suggest a pattern-recognition-based approach to myoelectric control, where each movement class corresponds to a degree of freedom of prosthetic control. This idea is by no means new; indeed, the first pattern recognition based control schemes were developed as early as the late 1960s and early 1970s [13]–[15]. These schemes used amplitude-based features and a simple statistical classifier to achieve reasonable accuracy (about 75% in a four-class problem), but used many myoelectric channels with cumbersome instrumentation, and required a large computing facility and lots of processing time. In the 1980s, the pattern recognition approach was refined somewhat by extracting more information (autoregressive coefficients) from fewer (two to four) myoelectric channels. This allowed greater accuracy (roughly 85% in a three-class problem), but the computing facilities of the day were incapable of achieving this task in real time. In the early 1990s, the accuracy of the pattern recognition approach was improved again with the use of artificial neural network classifiers [16]. This methodology was coupled with the use of transient signals (at the onset of motion), rather than the steady-state signals associated with a constant contraction to permit accuracy of roughly 90% in a four-class problem [17], [18]. This approach was implemented an embedded control system, easily meeting the real-time constraints of myoelectric control [19]. This technique employing transient signals was refined once again a few years later with the use of a wavelet packet based feature set, allowing the accuracy to approach 94% in a four-class problem [20].

The main drawback however, of using the transient MES as a control input is that it requires initiating a contraction from rest. This prohibits switching from class to class in an effective or intuitive manner. It severely impedes the coordination of complex tasks involving multiple degrees of freedom. For this reason, it is attractive to consider incorporating the strengths of pattern-recognition-based systems (accuracy and the ability to adapt to a user's intent) in a system allowing the steady-state signal to be analyzed in real-time. To this end, it was shown by the authors that a *continuous classifier* could be constructed, still retaining a very high level of accuracy [21]. This preliminary work demonstrated the feasibility and the potential of a continuous pattern recognition scheme; this paper explores its optimization with respect to accuracy, response time, and storage requirements.

III. Methodology

The construction of a continuous classifier and the acquisition of data used to evaluate it are described herein. The control problem can be defined for any set of motions. It was decided to investigate a four-class problem involving hand and wrist control, as those with below-elbow limb deficiencies represent a large proportion of prosthetic users. Four channels of myoelectric data were acquired using stainless steel bipolar active electrodes (Liberating Technologies, Hollington, MA). These were placed on the forearm above the wrist flexors and extensors, and on each side of the forearm, roughly equidistant from the elbow and wrist. Data were acquired from 12 normally-limbed individuals; each was instructed to perform wrist flexion, wrist extension, radial deviation and ulnar deviation with moderate force. No feedback was provided to regulate the force level. Each contraction was held for 5 s, and sampled at 1000 Hz using a 16-bit A/D converter, prefiltered between 10 and 500 Hz. This suite of four contractions was repeated 20 times.

Pattern recognition was performed on analysis windows that may be up to 256 ms in duration (a longer record would challenge the constraint of 300-ms acceptable delay). For each analysis window, a feature set was computed, and these features provided to a pattern classifier. The feature set consists of the time domain statistics originally proposed for transient signal classification [17], namely, the number of zero crossings, the waveform length, the number of slope sign changes, and the mean absolute value in each analysis window (see the Appendix for details). In [17], each window was segmented into multiple frames, and features computed on each, so that temporal structure might be captured. In this continuous classification scheme, however, the data are essentially stationary in any analysis window, so the feature set was computed on a single, unsegmented window. For the same reason, there is no advantage in using time-frequency methods such as the wavelet packet feature set, which was shown to be so powerful in transient signal classification [20]. Using the four-class data from 12 subjects, these simple time domain statistics were compared to the short-time Fourier transform, the wavelet transform, and the wavelet packet transform. The time domain statistics outperformed these other feature sets when processing continuous data.

A feature set was computed on each of four channels, and then concatenated to form a 16-dimensional feature vector. This feature vector was then provided to the classifier, which in this system is a linear discriminant analysis (LDA) classifier. More complex and potentially more powerful classifiers may be constructed, but it has been shown in previous work that the LDA classifier does not compromise classification accuracy [20]. The LDA classifier is also much simpler to implement and much faster to train. One half of the data were used to train the LDA classifier (the odd trials of the 20 repetitions of the four motion classes), and the other half (the even trials) used as a test set to evaluate the classifier's accuracy.

The continuous classifier acts upon a sliding window of data, producing a class decision (an estimate of the intended motion)

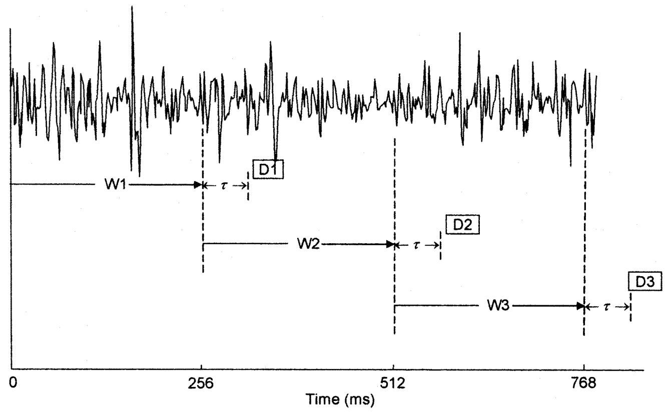

Fig. 1. Windowing of MES data in the continuous classifier. Successive analysis windows (W1, W2, and W3) are adjacent and disjoint. For each analysis window, a classification decision (D1, D2, and D3) is made τ seconds later, where τ is the processing time required of the classifier. Although four channels of myoelectric data are used, only a single channel is shown here for illustrative purposes.

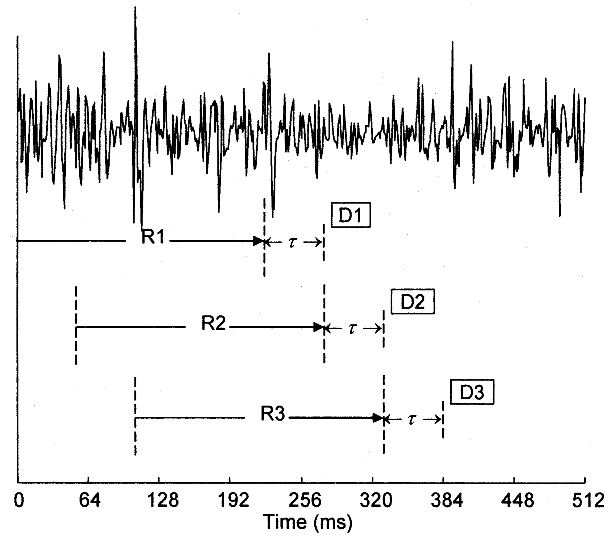

Fig. 2. Windowing scheme that maximally utilizes computing capacity and produces a decision stream that is as dense as possible.

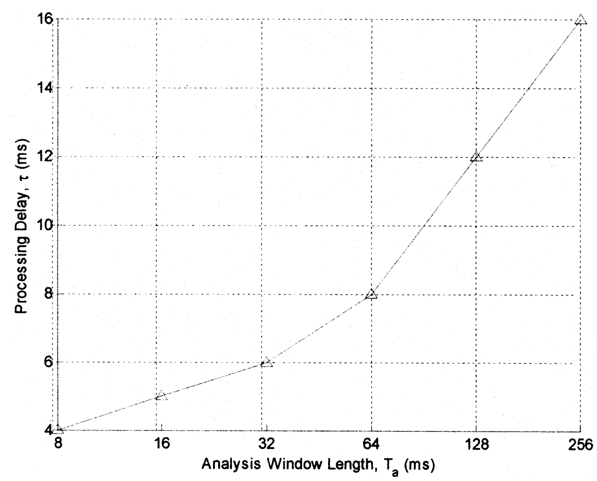

Fig. 3. Dependency between the analysis window length T_a and the processing delay τ. These results are for a 1-GHz Pentium III workstation using compiled Matlab code.

from each window. The simplest approach (that used in the original description of the continuous classifier [21]) is to use adjacent, disjoint analysis windows of the MES. This is equivalent to incrementing the window position by an amount equal to its size, as illustrated in Fig. 1.

In this scheme, each analysis window is equal to 256 ms (256 samples at 1000-Hz sampling). Therefore, decisions are made at 256-ms intervals, assuming that processing can take place while new data are being acquired.[1] The processing delay τ, as depicted in Fig. 1, consists of the time required to compute the feature vector and discriminate the data. Processing algorithms were implemented in Matlab, with computationally intensive portions compiled to increase speed. The processing was performed on a 1.0-GHz Pentium III based workstation.[2] For a 256-sample analysis window, this corresponds to a processing delay of roughly 16 ms.

It is clear from Fig. 1 that processing (feature extraction and classification) occurs in only a portion of the time spent acquiring data, implying that a processing system will be underutilized. Consider a scheme that fully utilizes the computing capacity of a given system: as soon as a decision is generated, begin processing the data of the most recent N samples, where N is the analysis window length. This is analogous to incrementing the N-sample analysis window by a time duration equal to the processing delay, as shown in Fig. 2.

This produces a decision stream that is as dense as possible,[3] given the processing capacity of the computing platform. This decision stream may be subject to postprocessing, intended to improve the accuracy of classification. It will be shown here that some distinct advantages result from this approach.

IV. Results

The data from the roster of 12 subjects were subject to analysis using the continuous classification algorithm. In this scheme the configurable parameters that will affect performance are as follows.

1) *Analysis window length* (T_a). This determines the amount of data used in feature extraction and classification, to produce one class decision. A larger amount of data will result in features with lower statistical variance and, therefore, greater classification accuracy. The tradeoff in increasing window length is the processing time required to generate a decision. This tradeoff is illustrated in Fig. 3.
2) *Acceptable delay* (T_d). This is the response time of the control system: the time from the onset of myoelectric intent until the control system is capable of generating

[1]This may be accomplished by insulating the processor from the data acquisition process, by means of direct memory access support.

[2]It is important to note that processing delays are relative to the coding efficiency and the processing power of the computing platform. The Matlab code used here is by no means as efficient as an implementation in assembly code or even C/C++. An embedded system would not likely be based upon a P-III microprocessor, but rather, a dedicated digital signal processing microprocessor. Regardless, the delays described in this paper easily scale to greater (or lesser) coding efficiency and computing power.

[3]It should be noted that this scheme requires that data acquisition and processing occur simultaneously, which is possible by separating the tasks into different threads of control.

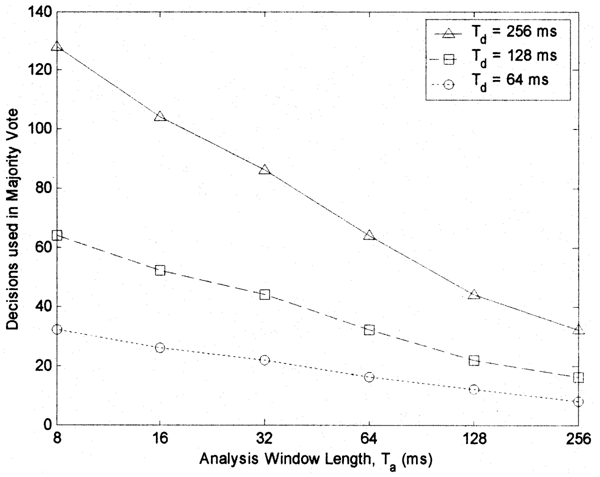

Fig. 4. The dependency between the analysis window length T_a and the number of decisions permitted in a majority vote decision. The results are shown for three different values of acceptable delay, T_d.

a class decision. If no postprocessing is performed, this is simply the processing delay of the system. If postprocessing is used, it is the period incorporating all decisions used. If a greater number of decisions are used in postprocessing, it will improve accuracy, but sacrifices response time.

The means of postprocessing the decision stream used here was a *majority vote*. For a given decision point d_i, the majority vote decision $d_{\rm mv}$ includes the previous m samples and the next m samples. The value of $d_{\rm mv}$ is simply the class with the greatest number of occurrences in this $(2m+1)$ point window of the decision stream. The number of samples used in the majority vote is determined by the processing time (τ) and the acceptable delay T_d. Specifically, if an upper bound on T_d is given (to meet a response time goal), then

$$\tau \cdot m \leq T_d$$

since one can only use the m decisions that follow the current decision, within a delay of T_d. The largest value of m to meet this inequality is used. For example, when using an analysis window length of $T_a = 256$ ms, we have $\tau = 16$ ms. If it is decided that the system will have a response time of no greater than $T_a = 128$ ms, then

$$16 \text{ ms} \cdot m \leq 128 \text{ ms}.$$

The largest value of m that satisfies this relationship is $m = 8$, so that $2m + 1 = 17$ decisions can be used in the majority vote. If one chooses a shorter analysis window, say $T_a = 32$ ms, the processing delay is $\tau = 6$ ms, which yields $m = 21$, allowing 43 points to be used in a majority vote decision. This interplay between T_a, T_d, and the number of decisions in majority vote processing is illustrated in Fig. 4.

During the evaluation of the classifier, each subject was instructed to perform each of the four motion classes for 5 s in sequence, as illustrated in Fig. 5. This example used an analysis window length of $T_a = 256$ ms, with an acceptable delay of $T_d = 128$ ms, allowing 17 unprocessed decisions to be used in each majority vote decision. Clearly, the majority vote processing has eliminated the spurious errors present in the unprocessed decision stream. Consider using a much shorter analysis window, $T_a = 32$ ms. This will produce features that are much more variable, which will degrade the classification accuracy of any single decision. In this case, however, the decision stream is much denser, and the majority vote processing can utilize more decisions (with $T_d = 128$ ms, 43 decisions can be used). This is depicted in Fig. 6.

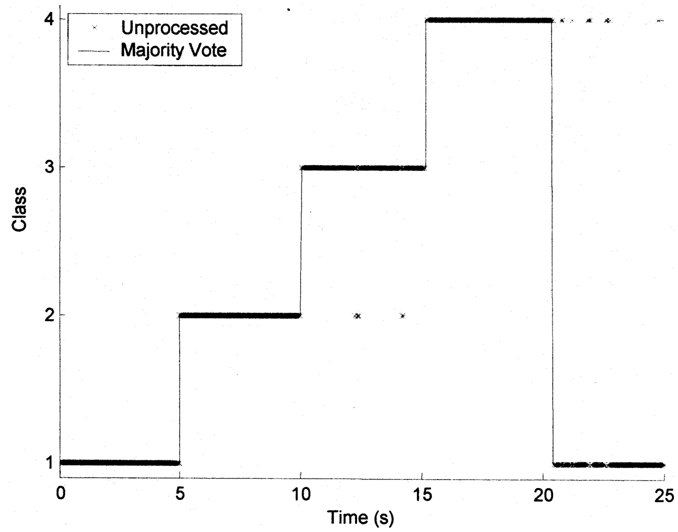

Fig. 5. The output of the continuous classifier for subject 1, using an analysis window length of $T_a = 256$ ms. The x's indicate the unprocessed classification decisions, spaced at $\tau = 16$ ms intervals. The solid line is the majority vote decision sequence, with an acceptable delay of $T_d = 128$ ms (17 decisions).

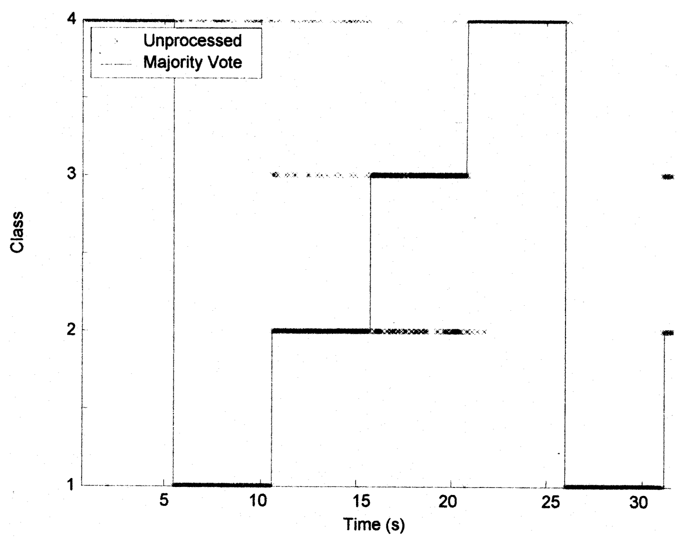

Fig. 6. Output of the continuous classifier for subject 1, using an analysis window length of $T_a = 32$ ms and an acceptable delay of $T_d = 128$ ms (43 decisions).

With this very short analysis window, the unprocessed decision stream contains a large number of errors, as expected. With the denser stream of decisions, however, the majority vote processing as capable of averaging out these errors. A complete picture of the effects of analysis window length and the acceptable delay upon classification accuracy is shown in Fig. 7.

As would be expected, the accuracy of the unprocessed decision stream degrades rapidly with decreasing analysis window length. If majority vote averaging is used, however, this degra-

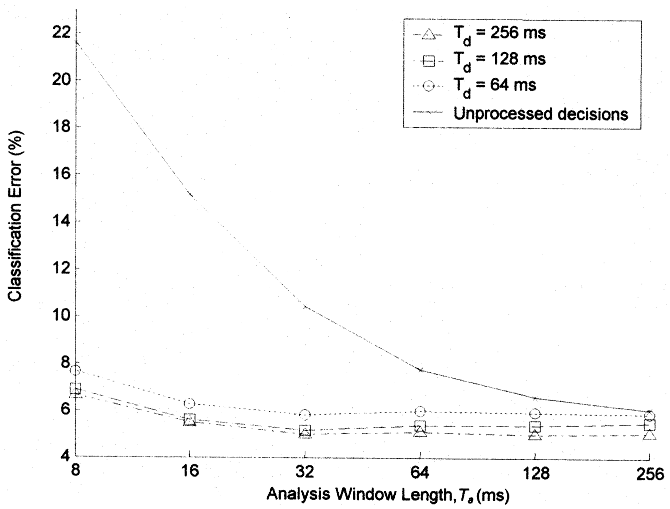

Fig. 7. Effect of analysis window length T_a and the acceptable delay T_d on the classification accuracy of the system. The error is expressed as a percentage, average over all 12 subjects.

dation is prevented, due to more decisions available with shorter windows, as demonstrated in Fig. 4. As expected, the performance increases as a longer acceptable delay is prescribed, as this allows more decisions in majority vote processing, at the expense of response time. Perhaps surprisingly, the best performance is with $T_a = 32$ ms. The implication is that, with a very short analysis window, accuracy is not compromised, and very little storage space is needed for the necessary computations. This is very important with regard to implementation of the classifier as an embedded system where memory is usually a scarce resource. Moreover, at $T_a = 32$ ms, the accuracy does not degrade substantially as the acceptable delay is reduced from $T_d = 256$ ms to $T_d = 128$ ms, allowing the system to be much more responsive.

V. Discussion

It is evident in Fig. 7 that the continuous classifier performs very well over a wide range of analysis window lengths, if accompanied by majority vote processing. It should be noted that the amount of data used to generate these results is quite substantial. For each of the 12 subjects, there were 4 classes $\times$ 10 trials $\times$ 5 s/trial. These 200 s of data are then subject to continuous classification, with results generated as quickly as the processing platform will permit. With an analysis window of $T_a = 256$ ms, we have a delay of $\tau = 16$ ms, which means that roughly 12 500 decisions will be made. With $T_a = 32$ ms $(\tau = 6$ ms$)$, roughly 33 000 decisions are made. These large numbers suggest that the classification accuracy determined for each subject is based on a rather large sample, and is likely quite stable.

Although it has been demonstrated here that this continuous classifier has some appealing capabilities, there are some issues yet to be resolved that are currently under investigation. These include the following.

1) No feedback was given to the subjects regarding the level of contraction, nor were explicit instructions given to maintain a constant level of activity. A prescribed force level was not desired for classification, since one would like to use the level of activity as a velocity control signal to the prosthesis. Upon inspection of the data used here, it is evident that the contraction levels do indeed vary substantially, suggesting that velocity control is indeed possible. Further experiments must be conducted to determine what dynamic range of contraction levels is possible, without significantly degrading classifier performance.
2) The system must know when to actuate the prosthetic devices, and when to suppress actuation. With a constant stream of decisions being produced, the actuation must be gated by some means. This might be accomplished by including an additional "inactive" class in the training session, by imposing a lower threshold of MES activity, or a combination of both. The development of this strategy is as important as classification accuracy in terms of usability.
3) The system has been shown to be very accurate in discriminating four classes of motion. Is it possible that combined motions (for example, hand close/wrist flexion) might be classified? This would enable simultaneous control of devices, which would enhance the anthropomorphism of control, offering benefits of functionality and dynamic cosmesis.
4) To what extent will additional channels of myoelectric activity improve the classification performance? Will a many-channel grid of electrodes offer the discrimination needed to resolve combined/simultaneous activities?

Although the performance of this control system has been described here, by means of classification accuracy, an ultimate test of controllability is in functional tests. Unfortunately, the continuous decision stream of this control system does not have an electromechanical counterpart than can exploit its high accuracy and response time. Powered wrists usually provide only rotation, flexion/extension; radial and ulnar deviation has been provided only by manual positioning. There are some dexterous hands under development [22], [23], but none are clinically ready. No current prosthetic solution is capable of actuating the number of classes and the response time offered by this control system, although this is the goal of a major European effort [24]. This has motivated the development by the authors of a computer workstation based "virtual prosthesis" that can actuate all degrees of freedom from the shoulder to the fingers. Functional tests based on this virtual environment are currently under investigation. An embedded implementation of the continuous classifier is also under development.

VI. Conclusion

The control of powered upper limb prostheses has not seen any revolutionary developments since its inception, but rather, incremental evolution. This paper represents progress toward a more natural, more effective means of myoelectric control by providing high accuracy, low response time, and an intuitive control interface to the user. It also offers parsimony of data storage and relatively simple signal processing, which is important in an embedded implementation. By exploiting the inevitable improvements in the processing capacity of computing systems, the accuracy of this system can be further enhanced.

APPENDIX
TIME DOMAIN FEATURES

Mean Absolute Value: An estimate of the mean absolute value of the signal $\mathbf{x}$ in segment i which is L samples in length is given by

$$\bar{\mathbf{x}}_i = \frac{1}{L}\sum_{k=1}^{L}|x_k| \text{ for } i = 1,\ldots,I$$

where x_k is the kth sample in segment i and I is the total number of segments in the record.

Zero Crossings: A simple frequency measure can be obtained by counting the number of times the waveform crosses zero. A threshold (ε) must be included in the zero crossing calculation to reduce the noise induced zero crossings. Given two consecutive samples x_k and x_{k+1}, increment the zero crossing count, if

$$\{x_k > 0 \text{ and } x_{k+1} < 0\} \text{ or } \{x_k < 0 \text{ and } x_{k+1} > 0\}$$

and

$$|x_k - x_{k+1}| \geq \varepsilon.$$

Slope Sign Changes: A feature that may provide another measure of frequency content is the number of times the slope changes sign. 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, the slope sign change is incremented if

$$\{x_k > x_{k-1} \text{ and } x_k > x_{k+1}\} \text{ or } \{x_k < x_{k-1} \text{ and } x_k < x_{k+1}\}$$

and

$$|x_k - x_{k+1}| \geq \varepsilon \text{ or } |x_k - x_{k-1}| \geq \varepsilon.$$

Waveform Length: A feature that provides information on the waveform complexity in each segment is the waveform length. This is simply the cumulative length of the waveform over the segment, defined as

$$l_0 = \sum_{k=1}^{L}|\Delta x_k|$$

where $\Delta x_k = x_k - x_{k-1}$. The resultant values indicate a measure of waveform amplitude, frequency, and duration all within a single parameter.

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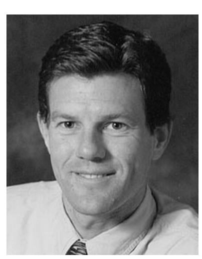

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