INPUT SIGNAL COMPLIANT METHOD FOR MYOELECTRIC CONTROL OF PROSTHETIC AND MEDICAL ROBOTIC ARMS

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Abstract

This paper presents an input signal compliant method for myoelectric control of medical robotic arms for amputees and paralytics. The approach is based on auto-regressive-integrated-moving-average (ARIMA) stochastic model characterization of myoelectric signals (MES).

The major concept centers on stochastic modelling of myoelectric signal (MES) temporal patterns. MES data samples are treated as time-series data. The data are parameterized, using ARIMA model identification methods. The resultant pattern vector consisting of ARIMA parameters is used to discriminate amongst several limb movements.

The overall approach combines spatial pattern recognition with time-series analysis to form what is termed here a spatial/temporal MES control methodology. This approach extracts the underlying characteristics of the bioelectric phenomena via statistical analysis and stochastic model characterization. The resulting features form a minimal parameter description of the original waveform. The ARIMA model is especially suited to characterizing the non-stationary myoelectric signal waveforms. The feasibility of ARIMA models for feature extraction is established for isometric muscle contraction at varying degrees of muscle tension. It is shown that for deltoid abduction at varying contraction levels (0% - 100%) two sets of ARIMA models, one for each muscle force range, can adequately characterize the movement. Within the framework of this study, the ARIMA model parameters are shown to provide highly diagnostic features that are consistent with feature selection criteria in the field of pattern recognition, i.e., low dimensionality, retention of sufficient information for recognition purposes, enhancement of the difference among the various classes, and comparability of features among classes.

The overall ARIMA model-based myoelectric controller system concept is described in terms of data acquisition, off-line identification and real-time operation. A discussion of the computational aspects of the ARIMA control concept and the engineering effort required for implementing a real-time microcomputer-based ARIMA controller is included.

This research and development work was supported by the Veterans Administration, Contract #101(134)P-778.

Introduction

Overview

This paper is organized into four sections. The first section provides a rationale for myoelectric control and reviews the literature in MES control methodologies. The second section summarizes the characteristics of the MES and provides a discussion of the use of Stochastic Model identification methods for feature extraction. In particular, it provides a description of feature set generation via ARIMA model identification. The result of a study that forms the basis for employing ARIMA modeling in MES characterization is also summarized in this section. The third section provides a description of the overall ARIMA model-based approach in the real time control of upper-extremity prosthesis. Included are the criteria for detecting the onset and termination of muscle activity, the ARIMA computational processes and their implementation. The concluding section provides a discussion of the joint signature analysis of MES from multiple electrodes.

Myoelectric Control

Myoelectric signals (MES) are the electric potential that accompany the contraction of a muscle. These signals can be measured by surface electrodes placed near the contracting muscle. This fact has prompted several researchers to investigate the potential of MES from selected muscle groups as a control source. The underlying hypothesis is that MES patterns from selected muscle groups are (a) highly correlated with specific limb movements and (b) contain sufficient information from which useful features can be extracted for distinguishing among possible arm movements. The obvious advantages of myoelectric control is that prosthesis task specification is at a natural and subconscious level. Further, since the signals are naturally correlated with arm movement, it is reasonable to expect that both the amount of training and concentration required of the amputee will be less than formidable.

Given the foregoing, the main issues surrounding the development of MES-controlled prosthesis are:

(a) Methods for determining when a movement commences.
(b) Methods for determining when a movement ends.
(c) Methods for characterizing (recognizing) the movement.
(d) Ensuring that processes associated with (a), (b), and (c) can be accomplished in near real-time.

Most MES control methods have been primarily ad hoc based on statistical features derived from stationary analysis methods of correlation functions and power spectral density evaluation (Kwatny, 1970; Radonjic and Long, 1970; Kriefeldt, 1971; Scott, et al., 1971).

Both parametric and nonparametric pattern recognition techniques have been applied in characterizing and classifying MES patterns. Wirta and Taylor (1970) and Herberts, et al. (1973) employed multivariate discriminant analysis. Lawrence and Lin (1972) and Lyman (1974) applied statistical pattern recognition methods. These approaches had some degree of success, but in each case several electrodes were required and their placement was critical. In certain cases, considerable computer capability was also required.

Kriefeldt (1971) employed signal processing and filtering methods to achieve a signal whose root-mean-square value was proportional to muscle tension. He studied several different kernels, including a first-order low-pass filter, a third-order Butterworth low-pass filter, and a third-order approximation to an averaging filter. The last turned out to be the most promising. However, the approach was limited to controlling only a few degrees of freedom.

Jacobsen (1973) postulated and showed for a two degree of freedom case that muscles in the clavicular regions of the shoulder reflect patterns of MES signals that can discriminate the state of the arm from shoulder to wrist.

Graupe, et al. (1975, 1976, 1978) employed autoregressive (AR) and ARMA time series models to characterize the recorded MES data. They justified their approach on grounds that the MES signal was wide-sense stationary and that one or more of the AR model parameters was relatively constant during the observation interval selected for the few limb movements they studied.

Madni (1978) proposed the use of Autoregressive-Integrated-Moving-Average (ARIMA) Models to describe the non-stationary MES waveform. This approach does not impose stationarity requirements on the MES waveform. The initial feasibility of the approach is established by the author on the basis of experimentation, statistical analysis, known signal characteristics, and linear stochastic model characterization of MES data.

MES Feature Extraction

Feature Extraction

The feature extraction or characterization problem can be generally stated as follows (Ho and Agarwal, 1968):

> "Given a pattern, signal or waveform, it is often convenient as well as necessary to convert the pattern, signal or waveform into a set of features or attributes that characterize the pattern under consideration. These features are usually denoted by the real variables $x_1, x_2, \ldots, x_3$ and the vector $\underline{x}$ is called the pattern vector. If we represent the original scanned pattern of sampled waveform as a vector $\underline{Z}$, then the characterization problem can be simply but vaguely stated as finding a map from $\underline{Z}$ to $\underline{x}$, i.e.,
>
> $$\underline{x} = \phi(\underline{Z}) \qquad (2.1)$$
>
> such that $\underline{x}$ adequately characterizes the original $\underline{Z}$ for purposes of classification but the dimension of $\underline{x}$ is smaller than the dimension of $\underline{Z}$."

Thus, the objective of a feature extraction and selection algorithm is to generate a new set of features that is consistent with the following four criteria:

(1) Low dimensionality.
(2) Retention of sufficient information for recognition purposes.
(3) Enhancement of the difference among the various classes.
(4) Comparability of features among the classes.

Usually, there is a loss of information in mapping the original pattern to a feature space of lower dimension. However, the amount of information loss can be controlled via judicious selection of features that retain sufficient information for class differentiation.

Characteristics of the MES

Myoelectric activity measured by surface electrodes is a function of the number and rate of motor neurons firing. The muscle fiber action potentials sum to produce the actual surface MES. The resultant signal appears highly random due to the random excitation of the many separate motor units action potentials that are present.

Previous investigators such as Kriefeldt (1971) have suggested that the root-mean square value of a suitably filtered MES is proportional to muscle tension, is repeatable, and hence constitutes a viable signal for prosthesis control. Bandpass filtering is recommended, with the useable frequency band of the measured MES estimated to be 100-1000 Hz. Since the signal power decreases at high frequency, the unavoidable presence of instrumentation noise explains the need of the high frequency cutoff. Low frequency cutoff arises from the fact that low frequency components are plagued by various sources of noise, e.g., motor-induced potentials between the skin and the electrode and polarization potentials.

It has also been proposed in the literature, in direct contradiction to the useful frequency band theory, that the predominant frequency bands for different muscle groups are different. Interest in the detection of energy bands was generated by observing the changes in MES before and during muscle fatigue. Specifically, the MES appears to be dominated by lower frequency components during fatigue (Kwatny, et al., 1970). Along the same lines, Person and Mishin (1964) observed that at first axis crossing the MES autocorrelation function moves outward with fatigue.

The main characteristics of the MES that can be identified from the study of these researchers are:

(1) MES is found to vary with different subjects, tension levels, muscle groups, and states of fatigue and higher order interaction among these variables.
(2) Recorded MES data also show variability with the type of electrode used.
(3) MES during muscle fatigue displays more power in the lower half of the spectrum, while MES before muscle fatigue has more power in the upper half of the spectrum.

None of these studies, however, provide insights into what features derived from muscle signatures can be used as diagnostic indicators of a given movement. This being the case, a reasonable initial hypothesis for facilitating feature extraction is required. Within the framework of myoelectric prosthesis control, most approaches have successfully utilized the fact that a particular movement is correlated with measured MES activity over muscles associated with that movement. A main question to be answered is to determine the extent to which MES may be used to infer the associated arm movements. The answer to this question hinges on addressing two key issues:

(1) Is there enough information in MES to unambiguously infer arm movements?
(2) Assuming there is, what is the optimum method for characterizing MES patterns that will facilitate MES classification in real-time?

The answer to the second question is the focus of this paper.

MES Feature Extraction Methods: A Historical Perspective

The stochastic nature of MES restricts the feature extraction/selection process to only mathematical features. The various models applied by researchers over the years have been primarily ad hoc. These models have included integrated rectified MES and variations thereof, root-mean-square value, zero-crossing density, peak height counting, frequency coding pulse counting, and combinations of the above (Lyman, et al., 1974; Basmajian, et al, 1975; Scott, et al., 1974). The problems with each of the above methods is that the specific features in each case capture only a limited amount of information from the original signal, and consequently, are not highly diagnostic indicators for limb movement discrimination.

More recently, time domain stochastic model characterization of MES has been pursued by researchers. In particular, rigorous time series analysis models such as autoregressive (AR) and autoregressive-moving average (ARMA) models were first suggested and employed by Graupe (1974) in characterizing the MES. The autoregressive model is applicable if the time series has an asymptotically zero mean and is asymptotically stationary. The authors justified the use of this model under the hypothesis that the MES is sufficiently stationary with a suitably selected observation interval for the limb functions they studied. However, the appropriateness of an ARMA representation in their study is somewhat questionable primarily because ARMA models are applicable in characterizing stationary time sequences only and MES temporal patterns do not exhibit stationary statistics. Further, if the time windown within which the model is fitted is made arbitrarily small so that stationarity-assumptions hold, there can potentially be a loss of highly diagnostic information.

Madni (1978) proposed the use of ARIMA models in conjunction with the spectral signature of the MES to describe the nonstationary MES waveform. This approach did not impose stationarity requirements on the MES waveform. In this study, the signals were collected with intramuscular wire electrodes from the deltoid muscle during repeated force-varying isometric abductions of the arm. The key findings of this analysis were that at most one differencing was required to induce stationarity in the MES data, the autoregressive coefficients were relatively constant within each of two tension ranges, and the tension ranges were separable on the basis of the percentage of cumulative power contained within experimentally determined frequency bands. This study forms the basis for the material presented in subsequent paragraphs.

Feature Extraction Via Stochastic Model Identification

Characterizing time series as a realization of a random process is a concept generally attributed to Yule (1978). A well-known property of stationary time sequences is that they may be represented by a linear filter model driven by white noise (Graupe, 1975). In particular, the process model must be BIBO stable (i.e., with poles outside the unit circle in the plane) for the output to be stationary. Further, by imposing the invertibility condition, i.e., the zeros lie outside the unit circle, the representation become unique. The essence of the modeling approach is the reduction of a random process to white noise (uncorrelated) residuals. The mathematical model of the time series is established by reducing the original waveform to white noise while identifying the correlated (predictable) portion of the time series. This approach differs from other known techniques in that no deterministic models of the time series (i.e., ramps or sinusoids) are initially assumed. The data are treated as a random process on which systematic application of time series techniques determines the desired mathematical model. If deterministic phenomena exists in the data, it is directly evident from the analysis without prior assumptions regarding their existence.

Linear Autoregressive-Integrated-Moving-Average Model

The general mixed autoregressive-moving-average (ARMA) model of order (p, q) is given by:

$$\boxed{x_K = \sum_{i=1}^{p} a_i x_{k-i} + w_k + \sum_{i=1}^{q} b_i w_{k-1}} \qquad (2.2)$$

Equation (2.2) is the general form of a linear stationary ARMA process. However, equation (2.2) is not directly applicable if the data exhibits nonstationary statistics. In certain instances, this difficulty can be overcome by removing the nonstationary sources of variation (Yule, 1927). For example, if the observed time series is nonstationary in the mean, then a single differencing of the series removes the nonstationary mean and the differences,

$$Y_k = x_k - x_{k-1} \triangleq \nabla x_k$$

(where ∇ is the backward difference operator) are found to have stationary statistics. If x_k is replaced by $\nabla^d x_k$ (where d is the number of differencing operations performed on the original data) in Equation (2.2), then there results a model capable of describing certain types of nonstationary time series. Such a model is called an "Integrated" model because the stationary model which is fitted to the differenced data has to be summed or "integrated" to provide a model for the nonstationary data. Writing

$$y_k = \nabla^d x_k$$

The general autoregressive-integrated-moving-average (ARIMA) model is of the form

$$\boxed{y_k = \sum_{i=1}^{p} a_i y_{k-i} + w_k - \sum_{i=1}^{q} b_i w_{k-i}} \qquad (2.3)$$

or in operator notation,

$$\boxed{a^p(B)(1-B)^d x_k = a^p(B)\nabla^d x_k = a^p(B) y_k = b^q(B) w_k} \qquad (2.4)$$

Where: $\{x_k\}$ is the orginal time sequence

B is the backward shift operator defined as $BX_k = X_{k-1}$

∇ = $1-B$, the difference operator

$a^p(B) = (1-A_1 B - A_2 B^2 \cdots A_p B^b)$ is the AR operator of order p

d is the number of differencing of the original data required to achieve stationarity

$\{Y_k\}$ is the d^{th} differenced data sequence with stationary characteristics

$b^q(B) = (1-b_1 B - b_2 B^2 \cdots b_q B^q)$ is the MA operator of order q

$\{w_k\}$, the white noise sequence is $\eta(0,\sigma^2)$

This model is referred to as a general (p,d,q) model, referring to a general (p^{th} order autoregressive, d^{th} data differencing, q^{th} order moving average) process (Box, et al., 1970).

The equivalent undifferenced model in the original time series $\{x_k\}$ is derived as follows:

$$Y_k = \nabla x_k = x_k - x_{k-1} \qquad (2.5)$$

Substituting Equation (2.5) into Equation (2.3) yields:

$$x_k - x_{k-1} = \sum_{i=1}^{p} a_i (x_{k-i} - x_{k-1-i}) + w_k - \sum_{i=1}^{q} b_i w_{k-i}$$

$$x_k = x_{k-1} + \sum_{i=1}^{p} a_i x_{k-i} - \sum_{i=1}^{p} a_i x_{k-1-i} + w_k - \sum_{i=1}^{q} b_i w_{k-i}$$

$$x_k = (1+a_1)x_{k-1} + (a_2-a_1)x_{k-2} + \cdots + (a_p-a_{p-1})x_{k-p} - a_p x_{k-(p+1)} + w_k - \sum_{i=1}^{q} b_i w_{k-i}$$

$$= \alpha_1 x_{k-1} + \alpha_2 x_{k-2} + \cdots + \alpha_p x_{k-p} + \alpha_{p+1} x_{k-(p+1)} + w_k - \sum_{i=1}^{q} b_i w_{k-1}$$

where: $\alpha_1 \triangleq (1 + a_1)$

$\alpha_i = a_i - a_{i-1} \ \forall_i \ i \neq 1$

$$x_k = \sum_{i=1}^{P+1} \alpha_i x_{i-i} + w_k - \sum_{i=1}^{q} b_i w_{k-i}$$

In general, if $y_k = \nabla^d x_k$ in Equation (2.3),

$$\boxed{x_k = \sum_{i=1}^{p+d} \alpha_i x_{k-i} + w_k - \sum_{i=1}^{q} b_i w_{k-i}}$$

ARIMA Model Feasibility

The feasibility of ARIMA Model Identification for feature extraction was explored by Madni (1978). The key elements of this study are provided in the following paragraphs.

The experimental data consisted of MES records from the deltoid muscle for different isometric contraction levels. These ranged from 0% to 100% (maximum), where 100% tension is defined as 100% of the force generated at maximum effort, not 100% of MES. The primary assumption in this experiment is that an X% run corresponds to X% of muscle tension which is proportional to abduction, and that the only muscle involved in abduction is the deltoid.

The results of the spectral analysis performed on the experimental data revealed a gradual but definite shift of power to lower frequencies with increase in muscle contraction (Figures 1-7). The total power of the signal was found to lie below 2500 Hz. The most significant shift of power to lower frequencies with increasing muscle tension was observed in the frequency band that contained ninety percent of the total power (see Table 1).

Ninety Percent of Total Power Frequency Range
As a Function of Muscle Tension Level

Muscle Tension Level	90% Total Power Frequency Band (Hz)
1	0 - 1190
3	0 - 950
5	0 - 650
10	0 - 550
25	0 - 530
50	0 - 510
100	0 - 400

Table 1

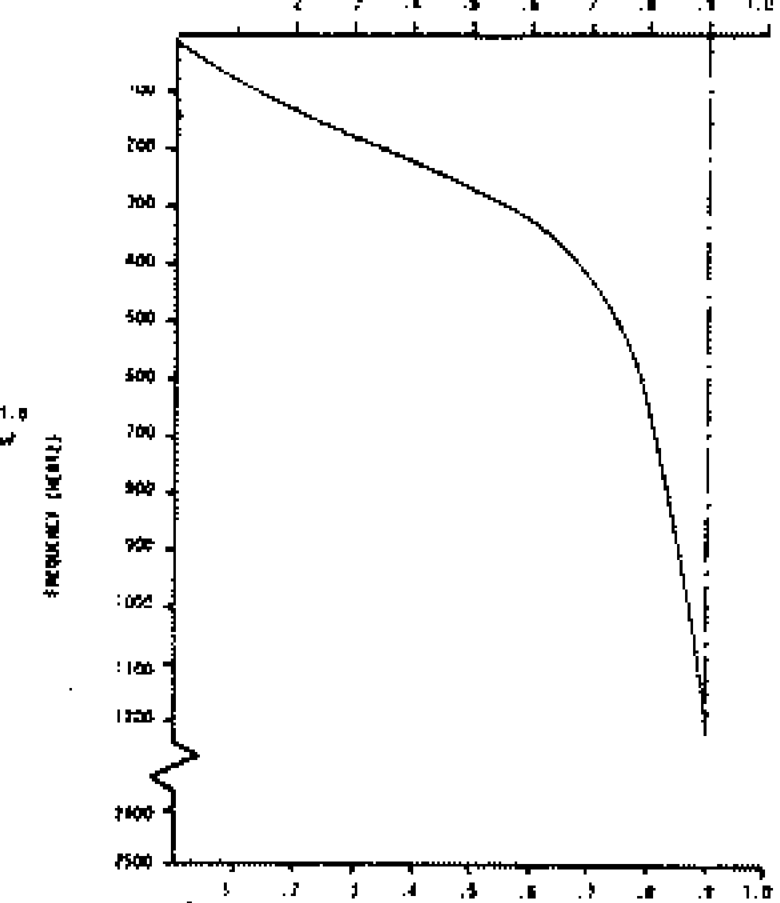

FIGURE 1.
CUMULATIVE POWER DISTRIBUTION
(1% CONTRACTION LEVEL)

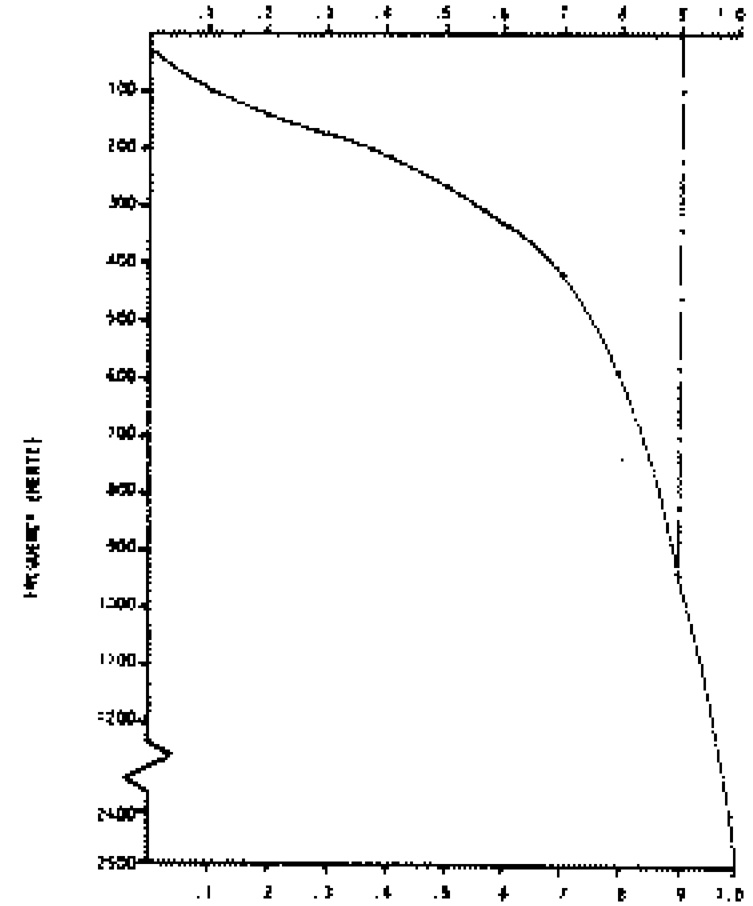

FIGURE 2.
CUMULATIVE POWER DISTRIBUTION
(3% CONTRACTION LEVEL)

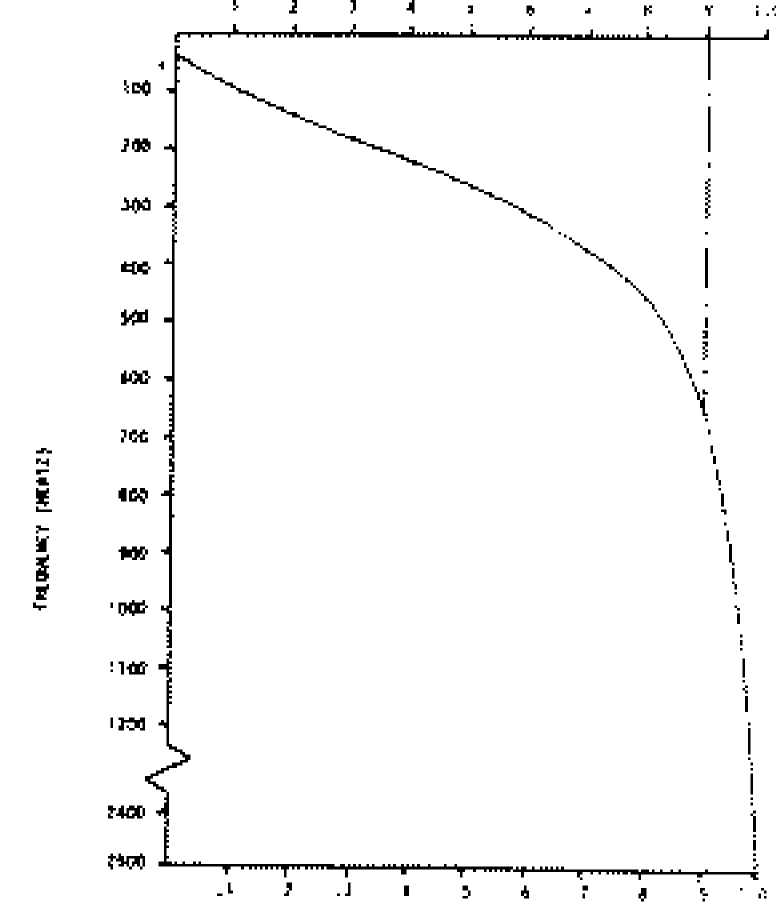

FIGURE 3.
CUMULATIVE POWER DISTRIBUTION
(5% POWER DISTRIBUTION)

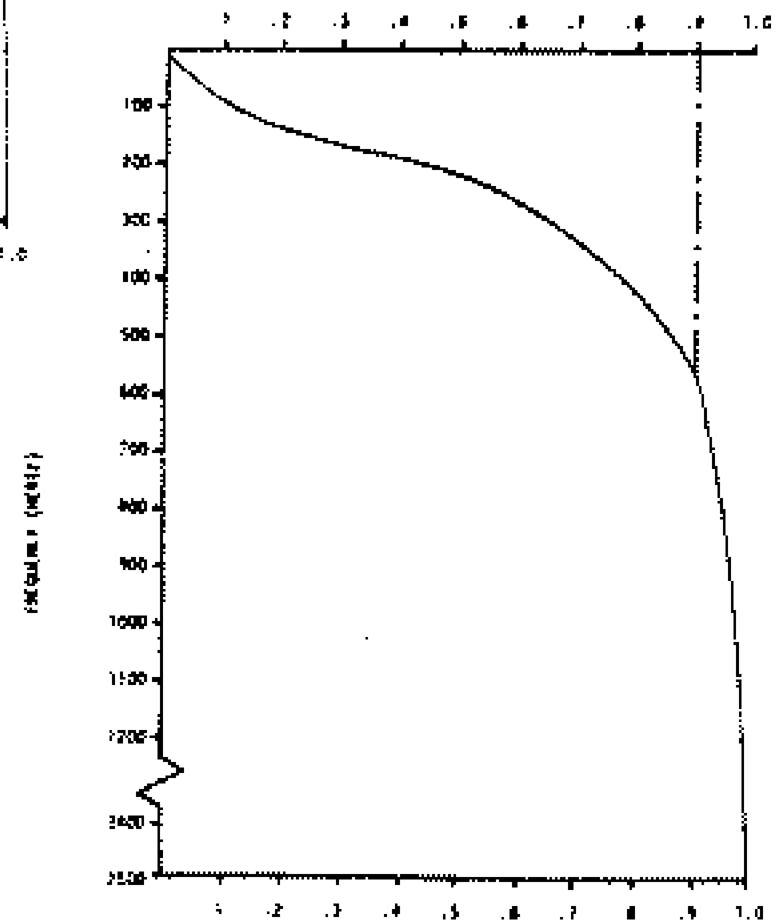

FIGURE 4.
CUMULATIVE POWER DISTRIBUTION
(10% CONTRACTION LEVEL)

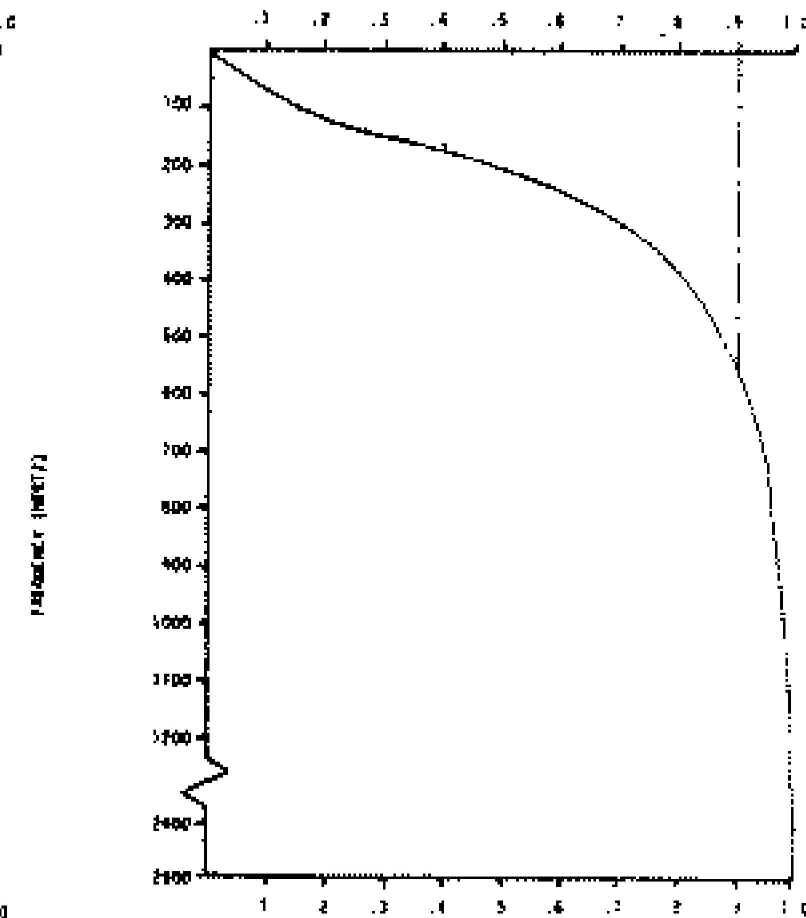

FIGURE 5.
CUMULATIVE POWER DISTRIBUTION
(25% POWER DISTRIBUTION)

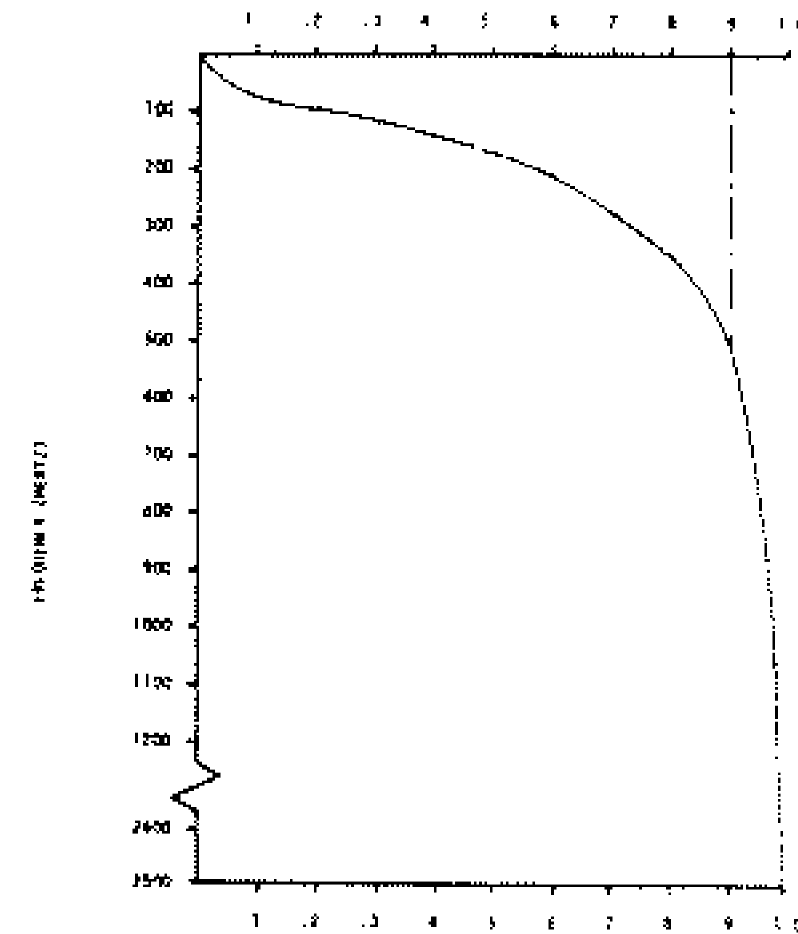

FIGURE 6.
(CUMULATIVE POWER DISTRIBUTION
(50% CONTRACTION LEVEL)

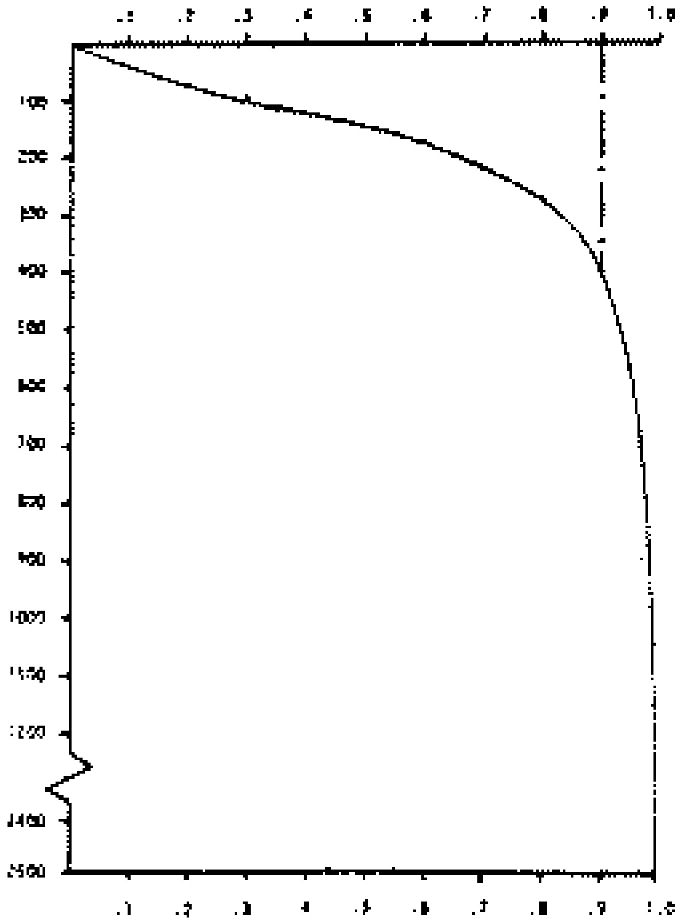

FIGURE 7.
CUMULATIVE POWER DISTRIBUTION
(100% POWER DISTRIBUTION)

Effect of Isometric Contraction on ARIMA Model Parameters

ARIMA models were fitted to the MES data recorded for each contraction level. The ARIMA parameters were averaged across the n trials for each contraction level. The following are the average pattern vectors for each contraction level.

	AR Coefficients			MA Coefficients		
$a_{1\%}$ =	[0.852	0.259	-.361	.058	.236	$-.216]^T$
$a_{5\%}$ =	[0.715	0.511	-.510	-.415	.215	$-.077]^T$
⋮						
$a_{50\%}$ =	[0.636	0.985	-.700	-.912	.270	
⋮						
$a_{100\%}$ =	[2.000	-1.084	.073	277	.475	

It is seen from the above results that the AR terms of the a vector do not change significantly for the 1%, 5% ..., 50% tension levels. However, the AR coefficients for the 100% tension level is quite different from those for all other tension levels (both in sign and magnitude). Thus, the contraction level ranges (within which the AR coefficients of the ARIMA pattern vector are relatively stationary) that result from this experiment are:

(1) 1% through 50% (or 'low') contraction range.
(2) 50% through 100% (or 'high') contraction range.

Each of these two contraction ranges can be represented by an average pattern vector. A question that arises here is how can one determine online the underlying contraction levels from the MES spectral signature. The results from the spectral signature analysis reveal that 90% of the cumulative power was below 400 Hz for the high tension case, but was above 400 Hz for the low contraction level case. This fact provides a useful criteria for determining whether a given MES pattern should be compared to the 'low' contraction pattern vector or the 'high' contraction pattern vector.

ARIMA Model-Based Myoelectric Control

Overview of Approach

The overall approach to real-time MES discrimination consists of signal conditioning and pattern recognition processes. The signal conditioning process consists of the usual preamplification, bandpass filtering, sample and hold and A/D conversion. However, the feature extraction and pattern classification processes which are central to MES control is where the bulk of the real-time implementation problems reside. The overall approach consists of two phases.

The first phase is the training phase. It consists of MES data recording and off-line model identification. In the data recording process, the raw MES data from multiple electrodes associated with a specific movement (e.g., deltoid abduction) is preamplified, bandpass-filtered and digitized. The digitized data from each of the electrodes is stored simultaneously along with the corresponding muscle contraction level. The off line model identification process consists of (a) power spectrum estimation and (b) ARIMA model structure and order determination, parameter estimation, model verification. The output of this phase will be pattern vectors for different limb functions. These pattern vectors will consist of ARIMA parameters for specific muscle contraction levels.

The second phase is on-line pattern recognition or the operational phase. In this phase, the MES patterns from the several electrodes are sampled, digitized and monitored for the onset of muscle activity. Several techniques have been used by researchers to detect the onset and termination of muscle contraction. The RMS power change is the criteria used in this methodology. Once the RMS detection circuitry indicates the onset of contraction, the data from each of the electrodes is recorded and stored until the RMS detector indicates end of the contraction. The stored temporal pattern is then compared to predicted oservations from each of the viable library patterns. The movement corresponding to the pattern that has the smallest residual is selected and specified to the appropriate actuators to produce the desired movement.

Computational Algorithms

Since ARIMA model identification is a computationally intensive process, the approach adopted in the Biotechnology Laboratory at UCLA in developing the UCLA-VA arm has been to derive the ARIMA parameters for each of the candidata limb movements in an off-line identification procedure. These parameters are stored for each electrode and limb movement combination and a given force level. In real time as a muscle contraction is detected, a series of parallel ARIMA filters are constructed from the stored coefficients to filter the MES time sequence. The residuals are then used to decide upon the intended limb movement. The pertinent equations for limb function classification are given in the real-time ARIMA controller flow diagram (Figure 8). The advantage of this approach is that the real-time processing consists of mostly filtering (comparing) incoming the MES data with each of the previously determined (off-line) ARIMA coefficient derived filters. This process is computationally far less intensive than real-time identification of ARIMA parameters. The algorithm does not require any divisions. Those terms that appear in the denominator are constants and their reciprocals can be taken off-line and stored in ROM. Provision of a hardware multiply chip can reduce multiplication time to negligible amounts. Consequently, the proposed implementation is well within the capabilities of today's 8-bit and 16-bit microprocessors.

Computer Memory and Timing Requirements

The MES data are sampled at 5 HKz for a maximum duration of 200 msec from 3 electrodes. Consequently, 1000 data points per electrode will be fitted using the ARIMA model. The resulting Random Access Memory (RAM) requirements

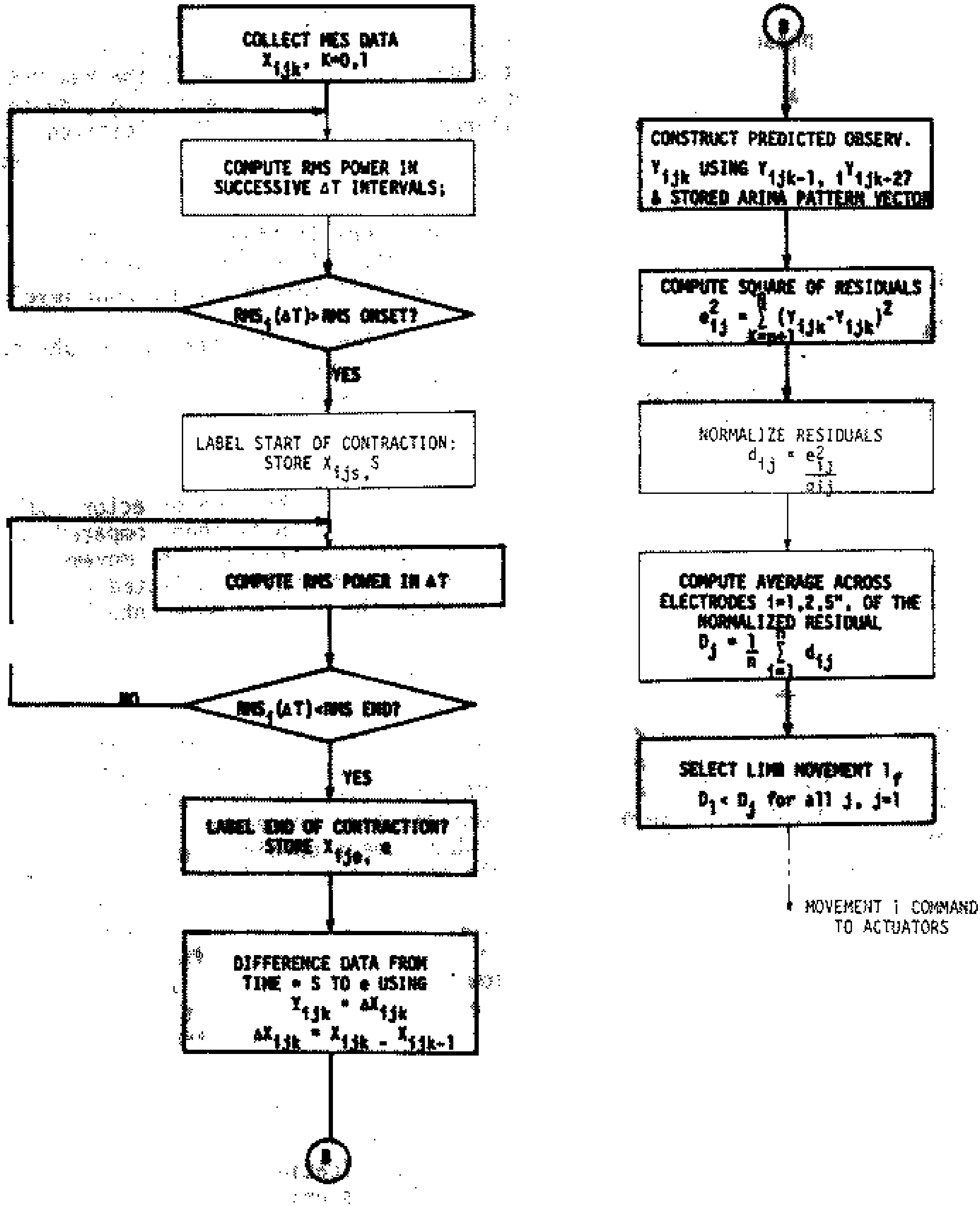

Figure 8. Flow Diagram of Real-Time ARIMA Controller

for this data including working memory is less than 8Kbytes. The Read Only Memory (ROM) requirements arise from the need to store ARIMA coefficients, residual variances and the differencing operations associated with each electrode site and limb function and the program. 4Kbytes of ROM is more than adequate for this purpose.

Present technology will allow conversion speeds of 15 μsec. Processing time required to sample 3 electrodes = 3 x 5.25 μsec = 15.75 μsec. Effective sample time = conversion speed + processing time = 15 μsec + 15.75 μsec = 30.75 μsec. Maximum sampling frequency = 1/30.75 μsec x 10^6 μsec/sec = 32520 Kz = 32.52 HKz. This is nearly 6 times the required resolution of 5 KHz.

On the basis of the equations in Figure 8, the ARIMA processing requires approximately 170 msec of a Z-80 microprocessor operating at 4 MHz. Consequently, 170 msec is the response time lag of the data acquisition system. This analysis is based on the hardware configuration in Figure 9. Further improvement in processing performance is achievable by selection of sophisticated processing based on more powerful processors.

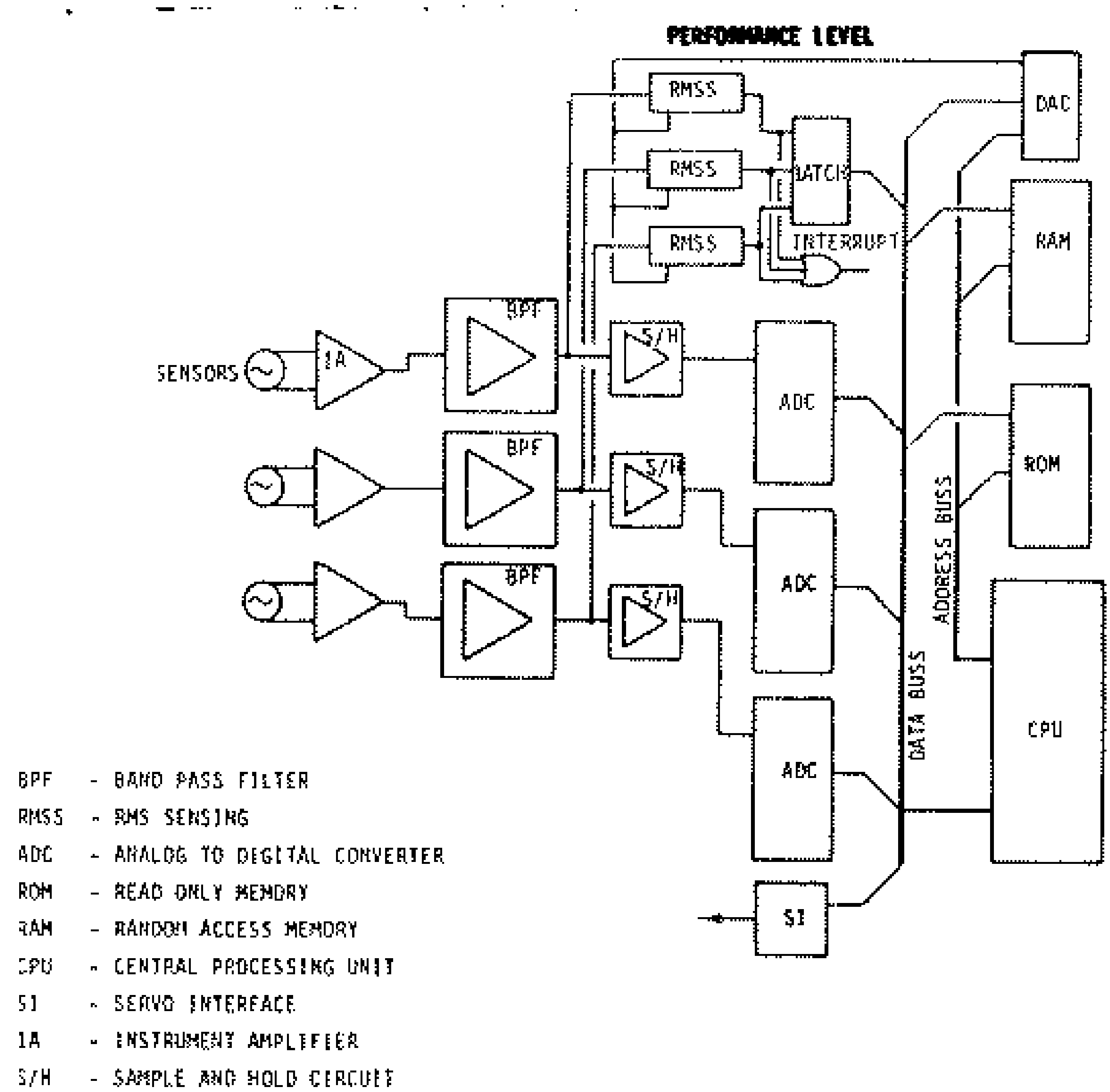

Figure 9. Arima Controller Hardware Configuration

Conclusions

Multi-Electrode MES Modeling

Past research in myoelectric control of upper extremity prosthesis has shown that recordings from just one electrode do not possess the necessary information for limb movement discrimination. Consequently, most researchers in the field today are concentrating on modeling temporal information from multiple electrodes in characterizing limb functions. While multiple electrodes were the basis for spatial pattern discrimination methods, their use in characterizing temporal signatures is relatively recent.

Graupe's (1978) approach is to analyze each electrode data separately. This author does not utilize the cross-correlation among the electrodes as a discriminating feature. Lindstrom (1974) showed that electrodes in different locations yield signals that are correlated. Therefore, a more promising way of viewing the multielectrode problem is to jointly characterize the MES waveforms associated with specific limb movements. In the context of MES characterization via ARIMA models, the new features would be the additional model parameters and residual variances resulting from each additional electrode and the cross-covariance or cross-correlation coefficient between pairs of electrodes.

The cross-correlation between multiple sites can be viewed as information or noise depending on the approach adopted. If each series was analysed independently then the cross-correlation would be viewed as "noise." On the other hand, if data from multiple sites was jointly characterized, then the cross-correlation coefficients would be considered a useful feature in discriminating among possible limb movement.

In any case, using the standard equations for computing cross-correlations may be quite inappropriate since, for moderately large values of N, e.g., N about 100, it is possible for two series which are actually uncorrelated to give rise to apparently "large" cross-correlation coefficients which are actually spurious unless a prefiltering process is performed on the original series (Jenkins and Watts, 1968).

References

(1) Box, G.E. and Jenkins, G.M. Time series analysis forecasting and control. San Francisco, California: Holden Day, 1970.

(2) Graupe, D., Beex, A.A.M., and Magnussen, J. On-line multifunctional prosthesis control based on identifying EMG signals using microprocessor hardware, IFAC Symposium on Identification, Tbilisi, USSR, 1976.

(3) Graupe, D. and Clink, W.K. Functional Separation of EMG signals via ARMA identification methods for prosthesis control purposes. IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-5:252-259.

(4) Graupe, D., Magnussen, and Beex, A.A. A Microprocessor system for myoelectric signal identification. IEEE Transactions on Automatic Control, 23:538-544, 1978a.

(5) Graupe, D., Parker, P.A., Stuller, J.A. and Scott, R.N. Comments on "Signal processing for the multistate myoelectric channel. Proceedings on the IEEE, 66:809-810, 1978b.

(6) Herberts, P., Almstrom, C. and Lawrence, P. Hand Prosthesis via myoelectric patterns, Acta Orthopedica Scandanavia. 1973, 44, 389-406.

(7) Jacobsen, S.C. Control systems for artificial arms. Ph.D. Dissertation, Massachusetts Institute of Technology Mechanical Engineering Department, January, 1973.

(8) Jenkins, G.M., Watts, D.G. Spectral analysis and its application. Holden Day, 1968.

(9) Kriefeldt, J.G. Signal versus noise characteristics of filtered EMG used as a control source. IEEE Transactions on Biomedical Engineering, January, 1971, BME-18, 16-23.

(10) Kwatny, E., Thomas, D.H., and Kwatny, H.G. An application of signal processing techniques to the study of myoelectric signals. IEEE Transactions on Biomedical Engineering, 1970, BME-17, 303-313.

(11) Lindstrom, L.H. and Magnusson, R.I. 1977. Interpretation of myoelectric power spectra: A model and its applications. Proceedings of the IEEE 65:653-662.

(12) Lawrence, P.D. and Lin, W.C. Statistical decision making in realtime control of an arm aid for the disabled. IEEE Transactions on Systems, Man, and Cybernetics, 1972.

(13) Lyman, J. Design approaches to adaptive control systems for arm prosthesis. Proceedings of the Association for Computing Machinery Conference, San Diego, California, November 11-13, 1974.

(14) Person, R.S. and Mishin, L.N. Auto- and cross-correlation analysis of the electrical activity of muscle. Medical Electronics in Biology and Engineering, 1964, 2, 155-159.

(15) Radonjic, D. and Long, C. Why myoelectric control is so difficult. In Advances in External Control of Human Extremities, Proceedings of the Third International Symposium on External Control of Human Extremities, M.M. Gavrilovic and A.B. Silson, eds., Belgrade, 1970.

(16) Scott, R.N. Myoelectric energy spectra. Medical and Biological Engineering, 1967, 3, 303-305.

(17) Wirta, R.W. and Taylor, D.R. Developments of a multiaxis myoelectrically controlled prosthetic arm. Proceedings of the Third International Symposium on External Control of Human Extremities, Dubrovnik, Yugoslavia, 1969.

(18) Yule, G.U. On the method of investigating periodicities in disturbed sines, with special reference to Wolfer's sunspot numbers. Philosophical Transactions, 1927, A226, 269-298.