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Pattern identification of electromyographic(EMG) signals in the lower arm

by

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INTRODUCTION

Myoelectric Prostheses

Mechanical cable driven arms are the most common and affordable upper limb prostheses, however, technology has progressed to the point where myoelectric prostheses (prostheses driven by electric motors and controlled by the EMG signals generated from an amputee's existing muscles) can better replicate the function of the lost limb with good patient acceptability. The two major design problems to be overcome with the myoelectric prostheses are an accurate and patient-acceptable control scheme and an effective feedback mechanism.

Myoelectric prostheses have many advantages and few disadvantages as compared to mechanical cable arms. Myoelectric prostheses can have more degrees of freedom than cable arms. Cable arms have only two, elbow flexion and pincer grasp. Up to eight degrees of freedom are possible in myoelectric prostheses. These are: hand grasp open/close, wrist adduction/abduction, wrist flexion/extension, wrist pronation/supination, humeral adduction/abduction, humeral flexion/extension, and humeral pronation/supination. An artificial arm of this complexity would, however, require an inertial platform, using accelerometers in three dimensions, in order to maintain constant hand orientation (Swain and Nightingale, 1980). Swain and Nightingale (1980) have developed a complete hand/arm control scheme involving sensory feedback, subconscious finger pressure, slip and torque feedback, trajectory mapping, and EMG pattern identification necesary for such a complicated prosthesis.

Jerard and Jacobsen (1980) developed a three degree of freedom arm with hand grasp activated by toe movement and elbow flexion with wrist rotation activated by myoelectric signals. Graupe, Salahi, and Kohn (1982) and Lyman, Freedy, and Solmonow (1977) experimented with similar three degree of freedom hand/arm prostheses, however, the toe was not used to control the hand function. EMG signals controlled elbow flexion and wrist rotation functions. Saridis and Newman (1979) built a hand/arm prosthesis with four degrees of freedom. Hand grasp, wrist rotation, elbow flexion, and humeral rotation were controlled by EMG signals in the shoulder or upper arm.

The myoelectrically operated arm provides excellent cosmesis (Shannon, 1979a, 1979c) and unencumbered fitting, important for patient acceptability (Domholdt, 1984). However, the lack of sufficient sensory feedback decreases patient acceptability. In an open loop system the operator is not aware of what the prosthetic arm is doing. Mental taxation due to the constant visual feedback required may result in its rejection by the wearer (Shannon, 1979c). Tactile sensory feedback in the form of electrocutaneous or mechanovibratory stimulation could be incorporated into the prosthesis design, eliminating the need for visual sensory feedback by the operator, thus improving acceptability.

Currently, myoelectric arms are considerably more expensive than conventional prostheses, but the costs will decline as technology and supply increase.

Goals

This paper involves pattern classification and identification of myoelectric signals in the proximal part of the forearm during specific movement of the hand and forearm. An unprocessed EMG signal has many components which can be incorporated for control of a myoelectric prosthesis. If these components can be classified and identified with reasonable success, a compact computer within a prosthetic arm can analyze the signals from the existing muscles on the stump of the amputee to control the prosthesis. This research attempts to utilize three of these EMG parameters, variance, zero crossings, and autoregressive (AR) correlation.

The goal is to find out which of the three parameters yields the most functional discrimination of six lower arm movements in a three degree of freedom system, and what maximal degree of functional discrimination can be achieved using a combination of all three. The motions involved are hand grasp and splay, wrist flexion and extension, and wrist pronation and supination.

Method

Major considerations in the data acquisition phase include minimizing artifact signals and noise in the input signal, designing the hardware for reduced size and power requirements (which would be necesary for EMG prosthesis circuitry), and microcomputer chip controllability.

With these considerations in mind, high input impedance FET Op-Amps were used for the high gain differential input amplifier, along with a single chip analog to digital converter. Including TTL control chips, all essential hardware fit on a 3"x4" prototype board. This includes two differential EMG amplifiers, a voltage comparator, a 4066 quad-analog switch, a 7404 quad-AND gate, and a 0804 A/D converter. This does not include the 6502 microprocessor and peripheral chips used in the PET Commodore computer chosen for this research. The PET was used because it utilizes integrated circuitry which could be redesigned as a dedicated computer contained inside the prosthesis.

EMG signals were taken from two electrode pairs, one pair on the skin over the digital flexors and one pair on the skin over the digital extensors. Two unimpaired subjects, a 21 year old female and a 24 year old male provided the EMG signals as a result of six different static contractions of the lower arm. Software was written in 6502 machine language to acquire, in real time, the digitized EMG signal and in PET BASIC to store it on a magnetic disk and analyze it. Variances, zero crossings, and AR coefficients were calculated off line. Then, decision planes were established in the feature space of variances, zero crossings, and AR coefficients. Accuracy in motion discrimination based on the three parameters was determined by acquiring a new set of test EMG signals and comparing them to the AR models and applying the variance and zero crossing decision planes. It was shown that variance and zero crossings yielded the best features with respect to functional separation.

LITERATURE REVIEW

Introduction

Myoelectric prostheses have been used by upper limb amputees for about 20 years. These prostheses were first controlled by EMG signal strength from one or more external electrodes located on existing limb muscles or adjacent shoulder muscles (Graupe et al.,1982). With improvements in technology, statistical features were realized as a practical approach to prosthesis control. Finally, with advanced technology, such as 16 bit microprocessors, previously time consuming temporal pattern identification and higher order statistics can be combined with a hierarchically intelligent control method to produce prostheses which will function smoothly with minimal mental taxation on the amputee (Saridis and Newman, 1979). A hierarchically intelligent control method is one where control signal determination is broken up into several levels. The output of each level in the command signal determination process is based on the output from the preceding levels, with EMG signals having the highest priority in the determination of the final prosthesis control.

Experimental Procedure

Soderberg and Cook (1984) list four components in the design of EMG instrumentation. These are: 1) the signal source, 2) the transducer, used to convert ionic bioelectric current to electron current, 3) the amplifier, and 4) the signal processing circuit.

Gross EMG signals result from the sum of many depolarizations of muscle fibers. Depolarization of these fibers results in their contraction. Muscle fibers contracting in groups cause specific limb motions to occur, with the application of force to a load as a result. Net force, therefore, is a function of many specific myofibril contractions and its magnitude is directly proportional to the number of myofibrils contracting. EMG signals must be reproducible over long periods of time for any particular motion. Almstrom and Herberts (1977) state this is in fact true. Gandy et al. (1980) show that for four muscles in the upper arm and shoulder, the shape and phase relationships of EMG signals collected periodically, with surface electrodes replaced each time, are clearly consistent over a period of six weeks.

Medeiros (1984), Soderberg and Cook (1984), and Graupe et al. (1978) state that a particular resultant limb movement is achieved through a complex combination of specific muscle group contractions. The limb movements are the result of synergistic EMG signals. This means individual muscle fibers cooperate to achieve an outcome (a limb movement) that would not be possible from the contraction of just one fiber. Although fine wire electrodes may be used to measure the potential of a specific muscle fiber or small group of muscle fibers, the measurement of just one or even a few myofibril potentials may not be representative of the function that is occurring. Reliability coefficients for fine wire electrodes, as reported by Soderberg and Cook (1984), are lower than for surface elctrodes. Within-day reliability coefficients averaged .62 for contractions ranging from 20 to 100 percent of maximum. Between-day coefficients averaged only .22 for the same range of contractions. This is due to the difficulty in placing the wire electrode in the same place each time. Since the electrode is so close to the signal source the small displacement of 5 mm or less which occurred with their use resulted in large differences in the readings. Movement artifacts are also introduced with the use of fine wire electrodes.

Surface electrodes have minor disadvantages but they effectively measure a gross EMG signal which is representative of the function taking place. Soderberg and Cook (1984) report for contractions of 30 to 50 percent of maximum, between-day correlation coefficients ranged from .78 to .95. Maximal contractions produced coefficients that ranged from .52 to .81. They also discovered that the largest signal for a bipolar electrode configuration was obtained near the center of the muscle with the electrodes oriented longitudinally with the muscle fibers. Medeiros (1984) found the optimized location to be oriented longitudinally but just off center of the "bulge" or the thickest part of the muscle. This may be true because the large movements at the "bulge" result in electrode movement. For electrodes placed with no more than 5 mm difference on the skin for between-day tests EMG signal parameters are not significantly different (Graupe, Salahi, and Kohn, 1982). A primary advantage of using surface electrodes is that they can easily be applied in a standardized manner with little discomfort (Soderberg and Cook, 1984). A primary disadvantage is that they may malfunction during heavy perspiration (Paciga, Richard, and Scott, 1980).

Electrodes must be nonpolarizable, so that half-cell potentials are not introduced. Most researchers cited use silver-silver chloride or gold-plated stainless steel electrodes. Stainless steel differential electrodes, 5 mm in diameter and spaced 25 mm apart, were used by van der Locht et al. (1980). Similar electrodes were used by Shannon (1979a, 1979b, 1979c), Soderberg and Cook (1984), and Doerschuk et al. (1983). Saridis and Gootee (1982) used gel-impregnated silver-silver chloride differential electrodes 1.75 inches apart separated by a center ground electrode. Gandy et al. (1980) and Medeiros (1984) used types similar to that used by Saridis and Gootee (1982).

Most authors cited recommend that the input impedance of the amplifiers ought to be at least ten times the maximum skin impedance. This reduces movement artifact and other distortions of the EMG signal. Van der Locht et al. (1980) state that this will decrease the inaccuracy of skin-resistance variations to approximately five percent or less.

Skin resistances can range from 200 Ω to about 2 M Ω. For measurement inaccuracies less than one percent an amplifier with an input impedance of 200 MΩ or larger is necessary. With the advent of very high input impedance amplifiers, silver-silver chloride electrodes in conjunction with electrolytic paste need not be used. Dry electrodes, which are much more comfortable, can be used quite effectively. Incidental movement of dry electrodes will not cause appreciable motion artifacts (van der Locht et al.,1980).

The maximum peak to peak voltage of raw or unprocessed EMG signals is 3 mV (Soderberg and Cook, 1984). This requires an amplifier gain of 4000 for a ± 6 V output. Typical gains range from 100 to 10,000 depending on the application. However, Paciga, Richard, and Scott (1980) used amplifiers with gains as high as 20,000.

It is generally recognized that most of the imformation in EMG signals is located in the range of 10 to 1000 Hz. This is corroborated by Shannon (1979a), Saridis and Gootee (1982), Soderberg and Cook (1984), van der Locht et al. (1980), Graupe et al. (1978), Gandy et al. (1980), Doerschuk et al. (1983), and Almstrom and Herberts (1977). The response of an amplifier should be uniform within this range. Shannon (1979a, 1979b, 1979c) uses amplifiers with a bandwidth from 10 to 500 Hz. Saridis and Gootee (1982) designed an amplifier with a gain of 5000, an input impedance of 22 $M\Omega$, and a bandwidth of 5 to 1500 Hz. Soderberg and Cook (1984) and van der Locht et al. (1980) state that to help eliminate cable artifacts, i.e., capacitance, the amplifier should be placed as close to the electrodes as possible. In fact, they, along with Shannon (1979a, 1979b, 1979c), incorporate a preamplifier into the electrode unit. This adds weight to the electrodes which might increase their incidental movement, causing motion artifact. This can be kept to negligible levels by minimizing the electrode/amplifier weight, securing it firmly to the skin, and using very high input impedance preamplifiers.

Since only the difference in potential between two electrodes is of interest, any signal common to both originates from outside the area of interest and should be discarded. Therefore, impedances on both inputs of the differential input EMG amplifier should be very nearly identical. This reduces the common mode rejection ratio (CMRR), defined as:

$$\text{CMRR} = 20 \times \text{LOG} \frac{A_c}{A_d} \text{ dB}$$

where A_c is the common mode gain and A_d is the differential gain. It is important to have a high CMRR with bioamplifiers because the body is a good conductor and acts as an "antenna" for many sources of electromagnetic noise such as from fluorescent lights, power lines, and other electrical equipment. These are the sources of unwanted 60 Hz noise. With the small EMG signals being measured such noise can have a significant effect. CMRRs should be at least 60 dB. Van der Locht et al. (1980) reported a CMRR of 100 dB.

Signal to noise (S/N) ratio is also an important specification of an EMG amplifier. Of the authors cited in this paper, only van der Locht et al. (1980) reported a S/N ratio. This was 60 dB.

Signal processing is the fourth important area to consider in bioamplifier design. Depending on the application, the raw EMG signal may be the desired form or a number of signal processing circuits may be employed. Soderberg and Cook (1984) give five possibilities. In addition to band pass filtering one may do further low pass (LP) filtering (smoothing), full wave rectifying, integrating over time, integrating in a time window, and integrating to a preset voltage followed by a reset. Most authors who base prosthesis control signals on EMG signal strength full wave rectify, LP filter, and (sometimes) integrate the amplified signal. One or more of these conditioning techniques are incorporated in the designs of Shannon (1979a, 1979b, 1979c), Medeiros (1984), Soderberg and Cook (1984), Paciga, Richard, and Scott (1980), and Almstrom and Herberts (1977).

Those authors who used digital signal processing and analysis did not use any of the above mentioned analog techniques. They were interested in recording only the unprocessed EMG signals. Various digital techniques were then employed to shape and modify the data. For example, Doerschuk, Gustafson, and Willsky (1983) digitally LP filtered the EMG signals with a half power frequency of 2.21 Hz. Other authors used moving average and absolute integral algorithms in their work (Sukhan and Saridis, 1982).

Discrimination Methods

EMG Signal Strength

Several parameters of EMG signals have been used as a measure of force or velocity in limb movements, as stated by Gandy et al. (1980). The mean level of the rectified and integrated signal, the averaged peak voltage, and the spike frequency are all approximately linearly related to muscle tension. Control of a myoelectric prosthesis using EMG signal strength was first suggested by Norbert Weiner in the late 1940s (Shannon, 1979a), but it was not until the 1960s that clinical prototypes were built and the 1970s that commercial hand/arm prostheses were made available.

One such device is the myoelectric hand created by Shannon (1979a, 1979b). It operated in an OPEN-CLOSE mode controlled by a threshold detector. It included a third mode, OFF (or HOLD), to make it a 3-state system. Figure 1 shows the rectified, LP filtered, EMG signal and the corresponding motor control signal. This system requires two discernible signal levels, V_c and V_o, be produced. Included is a noise threshold, V_{th}, which eliminates undesired prosthesis activation and built in hysteresis to smooth motor response.

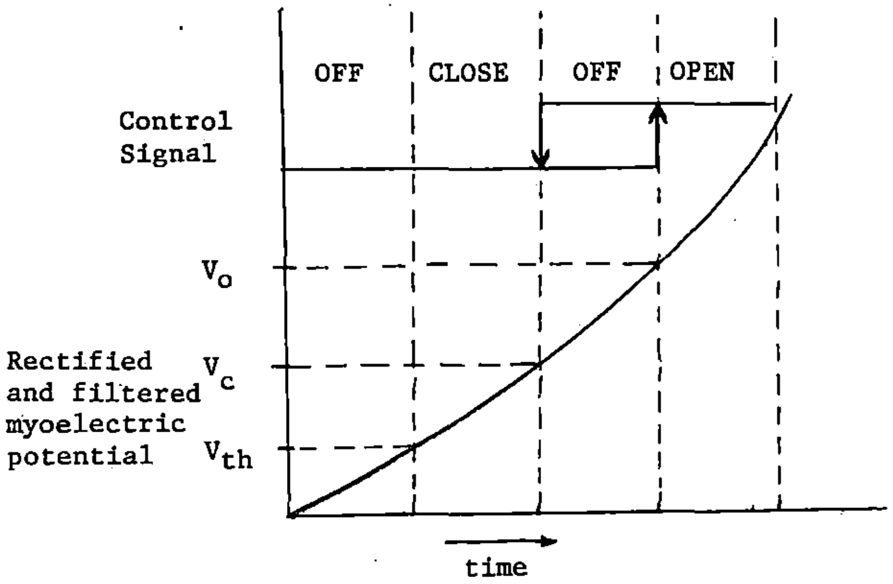

Figure 1 OPEN-CLOSE control system. Typical values of V_o, V_c, and V_{th} are 500 uV, 200 uV, and 50 uV respectively. The hysteresis creates an OFF range between the CLOSE and OPEN thresholds preventing erratic open and close activation.

A proportional control signal could be realized by taking the difference of two smoothed EMG signals from antagonistic muscles, i.e. the biceps and triceps. The sign of the result would indicate an OPEN or CLOSE mode while its value would indicate the speed of the motor (Shannon, 1979a, 1979b). Almstrom and Herberts (1977) mention that prosthetic hands of this type were commercially available in 1977. Paciga, Richard, and Scott (1980) employed a five-state system which would allow an amputee to control a two degree of freedom arm from one EMG site. Using their eyes for visual feedback, subjects tracked a computer controlled vertically moving horizontal line on a TV screen with a small circle projected on the screen. The small circle moved vertically in proportion to the angle of the elbow of a prosthetic arm attached to the stump of the amputee. Using the biceps brachii as the signal source, tests showed that a 1.1 % error rate resulted in tracking from one level to another with a total of five discrete levels. When the response of the circle was delayed by .2 s error rate was 6.6 %. It should be noted that in this study, which incorporated visual feedback, training for the task played a major role in the outcome. Training sessions, one hour long, were carried out twice a day, five days a week for three months. It is uncertain how much training would be required by an amputee using a prosthesis with a control scheme like this, but it might be prohibitive. It is apparent that some other control scheme is needed for easy, effective control of multi-degree of freedom prostheses.

Spatial Analysis

With the information obtained from more than one myoelectric site, control signals could be used to operate a multi-degree of freedom arm. Proportional control of an arm with more than three or four degrees of freedom would not be feasible with only two electrode pairs for each hand/arm motion as in Shannon's (1979a, 1979b) three state hand (Almstrom and Herberts, 1977). Thus, a spatial pattern identification method was implemented by Almstrom and Herberts (1977) using six electrode sites over existing muscles on the stump of a below-the-elbow amputee. An amputee can imagine a movement with his phantom hand, and in doing so he will contract his stump muscles in a way that is specific for that particular hand motion. Consequently, by applying pattern recognition techniques to the resulting EMG signals, the prosthesis control signals can be generated. The six rectified, LP filtered, EMG signals were recorded during six types of phantom hand movements and a computer calculated weighting factors for each electrode for each motion. The amputee then supplied test EMG signals which were multiplied by the respective weighing factors. If any values were greater than zero, the associated limb function or functions would be activated. They achieved good results both before and after training. Correct function discrimination for untrained patients averaged 88.6% while erroneous identification occurred 8.1% of the time. Trained patients had 98.3% correct function discrimination and 1.2% incorrect function discrimination.

There was no apparent attempt to optimize the weighting factors in their research. In fact, not much information was given stating the conditions under which the weighting factors were calculated. Identification could be optimized by not only training the subject to contract his muscle to agree with a group of weighting factors but to optimize the weighting factors during calibration (Jerard and Jacobsen, 1980).

Lyman et al. (1977) attempted to implement a proportional control scheme in a three degree of freedom arm. Nine electrode sites provided the EMG signals from both unamputated and amputated subjects. The signals were rectified, filtered, and sent through a threshold circuit to eliminate erroneous activation by noise. Goniometers were placed on the arm not used for EMG signals. The subjects then moved both arms simultaneously for each motion of interest. EMG signal patterns were correlated to goniometer movement by a digital computer during the calibration sessions. Movement trajectories were broken up into discrete segments, each characterized by its direction. Rather than determining the motion by application of weighting factors, Lyman et al. (1977) derived a set of probabilities from the EMG signal patterns and placed them in six matrices corresponding to the six motions possible. The decision criteria were based on Bayesian probabilistic measures. Function discrimination was achieved by parallel application of these probability matrices to the input signal, a method similar to that used by Almstrom and Herberts (1977) with weighting factors. Proportional control was achieved by converting the processed signal's spike frequency into pulse widths which were used to drive the motors directly. Just how electrode channel combinations were chosen for each specific motion was not described.

To facilitate more natural motion and less conscious effort by the operator, an adaptive "aiding" procedure was implemented to help determine the control function. The range of movement of each of the three joints was divided into 16 discrete segments. A computer "learned" those movements which frequently occurred. The computer then chose a set of possible directions and moved each joint in that direction which had a maximum probability of occurring, given the current position of the arm and the past directions from which the arm approached the current position (Lyman et al., 1977). These adaptive aided probabilities were constantly updated or "learned" when the arm was activated. After the initial learning period the prosthesis control was shared between the adaptive aided system and the amputee. Adaptive aiding acted as an independent automatic reflex. Since the research discussed by Lyman et al. (1977) was not completed when it was published no relevant results were reported.

Jerard and Jacobsen (1980) took a novel approach to prosthesis control by incorporating Newton's dynamic equations of motion. The relationship of the rectified, LP filtered EMG signals during static contractions to torque at the joints of interest was experimentally determined and placed in a matrix. Up to nine electrodes on the shoulder and upper torso were used to identify up to eight motions. An actual artificial arm was built with three degrees of freedom, humeral rotation, elbow flexion/extension, and wrist rotation. A matrix of control vectors, vector-myograms (VMGs), obtained from the EMG signal controlled motor activation. A technique called 'multivariable linear ridge regression' gave fairly reliable VMGs by discarding ill-conditioned data. This produced coefficients with a slight bias, but greatly reduced variance. To minimize the number of electrodes without reducing estimation accuracy, t values, a measure of the statistical significance of the regression coefficients, and cross correlations between EMG signals were found. If a t value with a probability of 95% or greater from a particular electrode was larger than 2 and the cross correlation to the signal from another electrode was greater than .8, then the associated vector coefficient contributed little to the function discrimination and the associated electrode could be removed. The number of electrodes was reduced to five.

The final limb movement occurred as follows. The processed EMG signals were multiplied by the experimentally determined vector coefficients establishing a set of VMGs which directed the prosthesis motion. The VMGs combined with current accelerations, velocities, and positions of the joints yielded the estimated torques that needed to be applied to each joint. The control signals were proportional to these estimated torques. Quantitative results were not presented. Jerard and Jacobsen (1980) did conclude, however, that the results were 'respectable' and further optimization of the procedure was merited.

Temporal Analysis

Time series analysis is another approach to EMG signal pattern identification. It is especially useful for amputees with severe muscle and nerve damage where few good myoelectric sites exist (Graupe et al., 1982). With spatial identification techniques a prohibitively large number of electrodes may be needed. This could be undesirable for the amputee since tedious daily fitting is necessary. Time series analysis requires only one electrode pair. Instead of comparing EMG output from one electrode to output from another, time series analysis compares the output from just one electrode at a point in time to the output from the same electrode at another point in time. Fourier transformation or autoregressive (AR) correlation can then be applied to identify the EMG signals.

Fourier transformation involves N x N computations where N is the number of samples. For a statistically significant number of samples this is too time consuming where on-line pattern identification should take no more than .2 s (Graupe et al., 1978). Because of its complexity none of the authors cited implemented fourier transformation into their EMG pattern identificaiton schemes. Soderberg and Cook (1984) did, however, discuss the potential of fourier transformation of EMG signals in therapeutics. The median or center frequency in the power spectrum remained relatively constant during brief contractions and decreased almost linearly with increased fatigue. Sherif et al. (1984) state that the power spectrum became more concentrated at lower frequencies when a muscle was dynamically contracted than when its contraction velocity was zero (static contraction). Doerschuk et al. (1983) state that the frequency spectrum changed with a change in the load. This may be useful in proportional control of myoelectric prostheses controlled by time series discrimination methods.

AR modeling is more applicable to EMG signal identification than other time series methods. AR modeling uses the EMG signal's statistical dynamics rather than its signal strength. Its advantage is that it requires only one electrode site. The disadvantage of AR modeling is that it requires more complex computation than other methods such as variance and zero crossing decision planes. The recorded EMG signal is essentially stochastic (composed of random error) which permits the use of AR modeling. The AR model is given by

$$y_m(t) = \sum_{i=1}^{p} A_{m,i}\, y_m(t-i) + e_m(t) \qquad (1)$$

where $y_m(t)$ denotes the EMG signal from the m-th limb function at time t, $A_{m,i}$ is the i-th AR coefficient for the m-th limb function, p is the order of the AR model, m is one of M limb functions, and $e_m(t)$ is white noise. AR correlation finds the relationships of a sample at time t to another sample at time t-1, and at time t-2, up to time t-p. A linear model is used and for it to be a good representation of the EMG signal the data are assumed to be a Guassian distribution (Graupe et al., 1978). That is , it is assumed that data at time t-i (i=1,2,...,p) are linearly related to data at time t with error in the form of white noise. Figure 2 shows a plot of arbitrary data at time t versus data at time t-1 (a first order AR model). Given y(t-i), y(t) can be estimated using the linear equation that best fits the data.

Time	Data(y_t)
0	4
1	7
2	8
3	9
4	10
5	8
6	5
7	3
8	1
9	2

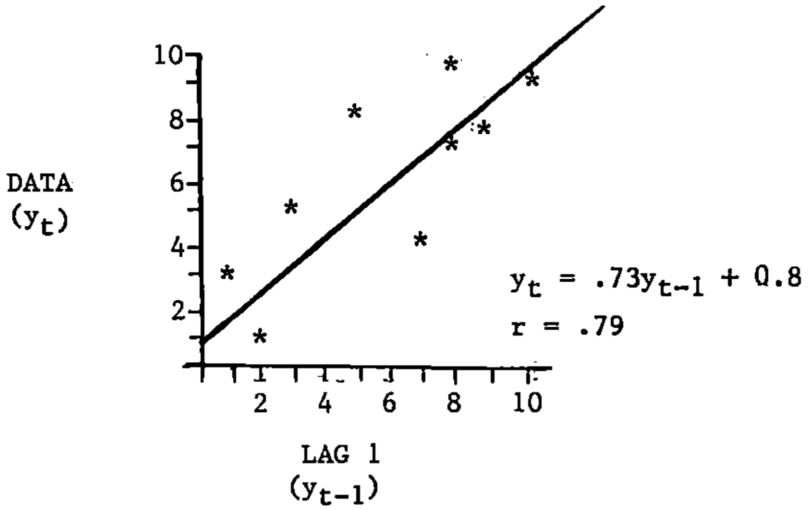

Figure 2 Sample AR modeling (single order, p=1). One statistical degree of freedom is lost for each order of the model, therefore N=9. r is the correlation coefficient of the best linear fit to the data.

The best linear fit is calculated by a least-squares algorithm. Least-squares is relatively insensitive to round off error and it requires the least number of samples for convergence (Graupe et al., 1978). This means that it greatly minimizes the AR coefficients for the higher order terms which in turn minimizes the white noise or cost functions $E_m = \sum_{i=1}^{N} e_m^2(i)$, where N is the number of samples (Doerschuk et al., 1979).

After the AR coefficients for each limb function are estimated (done off-line), testing of the model can begin. Since these coefficients are found off-line, calculation time is not an important factor. However, testing of these coefficients is done on-line and speed in function discrimination is essential. The N-p test data points are successively substituted into the M AR models which result in M predicted EMG values ($\hat{y}_m(t)$) at each time t, where p+1<t<N. The difference between $\hat{y}_m(t)$ and the actual EMG signal, $y_m(t)$, is $e_m(t)$. The sum of the squares of all the $e_m(t)$ terms gives an indication of the goodness of fit of the M AR models to the actual test EMG signal. This is represented by Equations 2, 3, and 4 below.

$$\hat{y}_m(t) = \sum_{i=1}^{p} A_{m,i} y_m(t-i) \tag{2}$$

$$E_m = \sum_{t=p+1}^{N} e_m^2(t) \tag{3}$$

where

$$e_m(t) = y_m(t) - \hat{y}_m(t) \tag{4}$$

Assuming one of the M motions is occurring E_m should be smallest and have a zero mean for that model which corresponds to the actual motion taking place.

Sherif et al. (1982) questioned the applicability of AR modeling to EMG signals because linear AR modeling requires the signal source to be statistically stationary and an EMG signal is not stationary. They also claimed an autoregressive moving average (ARMA) model was not a valid representation of a non-stationary stochastic signal. They suggested the use of an autoregressive integrated moving average (ARIMA) model. An ARIMA model was used by Sherif et al. (1982) because they were interested in modeling not just static contractions but initiation and build up of contractions to a maximum. They state that for some phases of contraction (static) an AR or ARMA model may validly represent the EMG signal. ARIMA modeling could differentiate between the different phases of contraction and reduce the number of coefficients needed to accurately model the EMG signal. Sherif et al. (1984) sampled data at 2000 samples/s during continuous humeral abduction/adduction. The resulting sample record was segmented into a series of subrecords, each .05 s long and considered stationary. After application of the ARIMA algorithm, AR and moving average coefficients resulted. The work of Sherif et al. (1982) was to demonstrate the applicability of ARIMA modeling of EMG signals. Quantitative results of motion discrimination accuracy were not presented.

Graupe et al. (1978) was the first to develop an AR algorithm for EMG discrimination. For small increments of time, i.e. .05 s, the EMG signal was be considered stationary and an AR model was applicable (Graupe et al., 1978). Graupe et al. (1978), somewhat arbitrarily, decided on .2 s as the maximum time allowed for function discriminaton by the computer. At a sampling rate of 5000 samples/s and increments of 200 points a .04 s sampling window resulted.

Graupe et al. (1978) used a third order AR method similar to the one described above. Off-line they calculated the error, $\overline{S_m}$, between the AR model and the calibration data used to find the AR coefficients. During on-line testing if $E_m < \rho_m \overline{S_m}$ the m-th limb function was chosen. The term ρ_m was an arbitrary value intended for optimizing the discrimination accuracy. It had no physical/intuitive meaning (Doerschuk et al., 1983).

If the signal energy $E = \sum_{t=1}^{N} y^2(t) \geq E_{th}$, where E_{th} is the minimum energy threshold, the m-th limb function was activated. Four limb functions could be discriminated with an 85% success rate using a single electrode pair in the work of Graupe et al. (1978).

Graupe and Salahi (1979) used four AR parameters and signal variance for function discrimination. Instead of using the parallel filtering identification method of previous work by Graupe et al. (1978) a new classification method replaced it. AR coefficients were found on-line and compared to reference parameters estimated during a calibration procedure. If the first AR coefficient's absolute value was within a predetermined distance of the first reference AR coefficient for each of M motions, then the second coefficient was tested. If all coefficients were within the pre-specified range of the reference coefficients for the m-th function, that function was activated. Graupe and Salahi (1979) incorporated a second electrode pair to increase discrimination accuracy. Discrimination of the signal from the second electrode pair was used to verify discrimination from the first. Graupe and Salahi (1979) obtained a 99% success rate in identification of four limb functions.

The calibration training procedure was found to be of major importance for the system's performance. The subject learned to contract his muscles so that he could reproduce consistent AR parameters from which the reference set was derived. This biofeedback method preserved the integrity of AR modeling only if the subject learned to contract his muscles subconsciously as in the contraction of a normal arm.

Graupe et al. (1982) used the same function discrimination method as Graupe and Salahi (1979) plus an additional method. Vector space of several parameter combinations yielded further discrimination accuracy albeit at the expense of computation time. For example, feature space of the second AR coefficient (A_2) versus the first AR coefficient (A_1), with decision planes determined off-line, could assist in the discrimination of two or more limb functions. Graupe et al. (1982) reported that with training (up to 12 hours) the subjects could consistently reproduce A within 10% of the same value. They achieved a 99% accuracy rate with six limb functions.

In the work of Graupe et al. (1978), Graupe and Salahi (1979), and Graupe et al. (1982) no results were given on discrimination accuracy if the reference criteria from more than one limb function were satisfied simultaneously.

In the work of Doerschuk et al. (1979) data were not acquired in lump sums as with Graupe et al. (1978). A 2000 Hz sampling rate was used and motion discrimination occurred every .05 s after each new data point was taken. Pattern identification was based on a moving 401 point sampling window. This seems to have ignored the non-stationary nature of EMG signals since the sampling window was .2 s wide.

Doerschuk et al. (1979, 1983) employed an AR model similar to Graupe et al. (1978), however, instead of determining discrimination based on a threshold they developed a set of probabilities based on the AR model error $\overline{S_m}$ and AR coefficients $A_{m,i}$. Then the prediction error $e_m(t)$ was computed, given by Equation 4. If limb function m was, in fact, taking place, then $e_m(t)$ was (ideally) a white noise process and that limb function should have had the greatest probability of occurring.

Four electrode pairs placed 90° apart around the forearm provided the EMG input. Varying load was not dealt with and the shape of the EMG spectrum was assumed independent of the load. This also assumed the AR coefficients did not change with load. Six limb functions were divided into four different phases. These were rest, initiation of function, hold, and return to rest. It took eight seconds to complete each cycle.

Probabilities for one motion, during the hold phase, were as high as .96 with the other five motions making up the difference. Since it was assumed that one of the six motions was always occurring the sum of the probabilities equaled 1.0 and one function always had the largest probalility even if no signal was present. Therefore, a fifth electrode was used to determine signal strength. If the signal was greater than a predetermined threshold then the limb was actuated. It appears that Doerschuk et al. (1979, 1983) defeated the purpose of having few electrode sites in AR modeling by using five electrodes. Medeiros (1984) stated that the optimum myoelectric site was directly above the muscles associated with the limb movements of interest. Optimization of muscle sites might have been achieved by Doerschuk et al. (1979, 1983) by placing the electrodes directly over the muscles that were most closely associated with the motions of interest.

Saridis and Gootee (1982) combined variance and zero crossings with AR correlation. They found more class discrimination information was contained in variance and zero crossing than in AR correlation. Twenty-six motions and one rest state were discriminated in a three degree of freedom system (humeral rotation, elbow bend, and wrist rotation). The 26 motions included the six single or primitive motions, all 12 possible double motions, and all 8 possible triple motions. The EMG signal parameters were evaluated for their ability to separate the 27 classes from each other. Only 65% of the classes were separable from each other. After incorporating a "learning" function into the discrimination scheme and using only variance and zero crossings, 85% of the classes could be separated from each other with less than 10% error. Some of the motions with misclassification error greater than 10% were incompatible with each other. This means it was improbable for some motions in an arm to occur depending on the previous motion. The incompatible combinations could have been identified by the on-board computer and not activated.

Sukhan and Saridis (1982) developed a proportional control scheme using variance and zero crossings as the best features for motion and speed separation. The integral absolute value (IAV), defined as the time integral of the absolute value of the signal, was the only feature directly extracted from the EMG signal for pattern identification. Sukhan and Saridis (1982) found the relationships between IAV, variance and zero crossings which provided translation from one feature space to another.

Saridis and Gootee (1982) observed certain superposition properties of combined motions allowing decomposition into the six primitive motions making class separability an easier task. Sukhan and Saridis (1982) also developed a decomposition scheme in their work. Rather than create a set of decision planes they established a set of reference probabilities for each of 27 motions and three speeds. Ten samples of each of the 27 motions and three speeds were used to calculate the reference probabilities. The test EMG signal was converted to the feature space of variance and zero crossing. One of 27 motions, including rest, was determined then the EMG signal was decomposed into the primitive motions with an associated speed. This could then be used to actuate the motors of an artificial arm. A learning procedure was provided which updated the reference probabitites as the arm was activated, similar to Lyman et al. (1977). Computer simulation resulted in a 90 to 97 percent accuracy rate. Results of an actual clinical model were not presented.

Command Languages

Although most of the EMG signal identification methods are reasonably accurate they may not generate control signals that result in natural or cosmetically acceptable movement of the prosthesis. Control languages can assist in motion discrimination and relieve the wearer of constant mental attention by becoming an autonomous control system requiring only supervisory intervention (Swain and Nightingale, 1980).

In the scheme proposed by Swain and Nightingale (1980), commands were supplemented by signals from an array of sensors in the hand relating to static and dynamic relationships between the hand and the object being gripped. The overall system was a hierarchy in which functions were initiated at a conscious level, but were performed without conscious effort.

Four inputs were needed to control a nine degree of freedom system (six degrees of freedom in the arm and three degrees of freedom in the hand). The hand was controlled by signal strength from a single EMG electrode. Six discrete EMG signal levels were required to control wrist flexion/extension, wrist rotation, and grasp. Location of the EMG electrode site was not mentioned. A set of commands such as HOLD, SQUEEZE, and RELEASE were generated and were manipulated by the feedback mechanisms and the current position of the arm. The arm was controlled by three sensors detecting body movements, presumably from the shoulder, and control algorithms generated the required joint angles. Swain and Nightingale (1980) claimed that flexibility could be achieved with "very little prior training." Clinical testing of a complete prototype had not yet begun as of the writing of the paper by Swain and Nightingale (1980).

A syntactic approach to prosthesis control was proposed by Saridis and Newman (1979) and Saridis et al. (1979). This system was designed for a four degree of freedom arm (humeral rotation, elbow flexion, wrist rotation, and hand grip) where the entire range of each of the four joints was divided into discrete increments. Command signals directed each joint to hold the current position or move one increment in either direction.

Command strings would be generated from statistical features of EMG signals during specific phantom hand/arm motions via a three level hierarchical control scheme. The first level would extract the pertinent features, identify the limb function, and decompose the EMG signal into its primitive motions and speeds (Sukhan and Saridis, 1982). The second level would include a learning procedure and determine the desired trajectories based on the output from the first control level, automatic sensory feedback, and previous movement and position of the arm. The third level would generate the necessary control signals to activate each motor based on the desired trajectories and the information obtained from the first level. Research on level one of this prosthesis control scheme was discussed by Saridis and Gootee (1982) and Sukhan and Saridis (1982). A possible hierarchical intelligent control scheme for level two utilizing "high-level decision languages" was discussed by Saridis et al. (1979). Results of a final system's performance were not reported.

EQUIPMENT AND PROCEDURE

Description of Hardware

All aspects of the hardware were designed with the capability of being contained in an actual prosthetic arm. The hardware circuitry was composed of three main sections, analog processing, digital processing, and data feedback. Only the first two were required for control of a prosthesis. The latter aided in laboratory evaluations of the system. The information processing block diagram is shown in Figure 3.

FET Op-Amps were choosen for the EMG amplifier because of their low power requirements and very high input impedance. Appendix A shows details of the EMG amplifier design. Using two single chip quad op-amps, two differential amplifiers were built with gains of 4700 and -3dB bandwidths of 5 Hz to 960 Hz. This coincided with the requirements specified by van der Locht et al. (1980) and Soderberg and Cook (1984). CMRR was approximately 90 dB for both amplifiers and S/N ratio using a 400 Hz test signal was 45 dB. Signal to noise ratio is defined as

$$\frac{S}{N} = 20\text{LOG}\,\frac{V_s}{V_n}$$

where V_s = peak to peak voltage of the signal output and V_n = peak to peak voltage of the noise output when all three leads of the amplifier are grounded.

The op-amps were powered by +9 V and -9 V sources, using 9 V batteries to improve safety. The circuit had an inherent DC error in the last amplification stage. This was eliminated by including a DC offset.

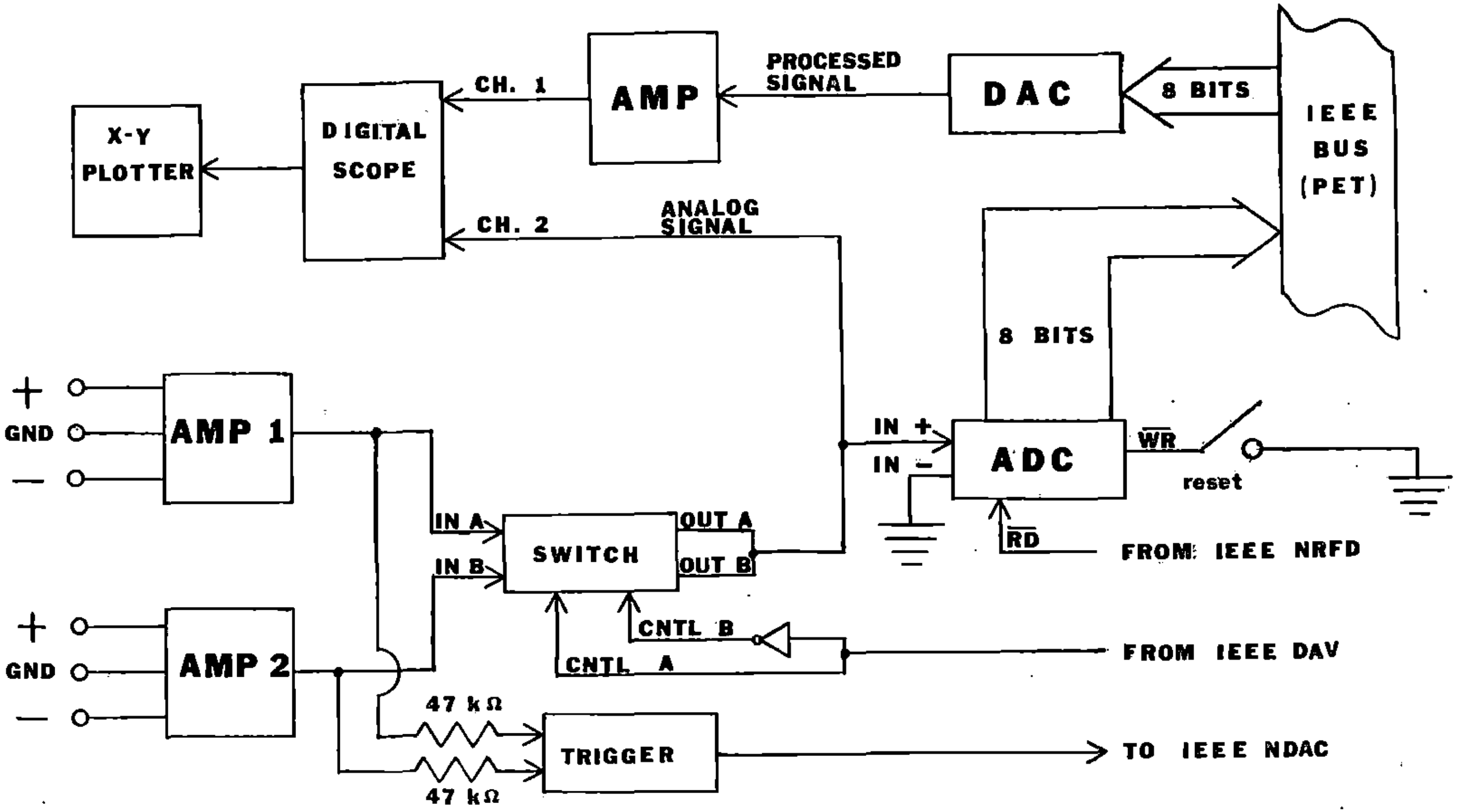

Figure 3. Block diagram of the hardware system. AMP 1, AMP 2, and trigger represent the analog processing section; ADC is the digital processing section; and DAC, AMP, the digital storage scope, and the X-Y plotter are the data feedback section.

Silver-silver chloride gel impregnated electrodes with adhesive perimeters were separated 1.25 inches by a center ground electrode, similar to the method used by Saridis and Gootee (1982). The geometry of the electrodes is shown in Figure 3A.

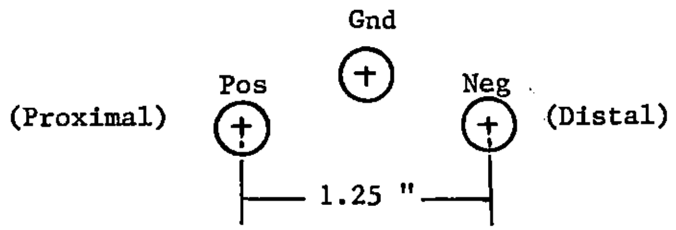

Figure 3A Schematic of the differential electrodes. The negative terminal was placed distally on the forearm for all samples for both the flexor electrode and the extensor electrode. The silver-silver chloride electrodes were held together by adhesive backing.

One of these electrodes was placed over the flexor muscles and one over the extensor muscles on the proximal part of the forearm. The amplifier system was designed for use with dry electrodes, however, gel electrodes were considered sufficient for experimental purposes. The adhesive surface firmly secured the electrodes to the skin and helped reduce artifact noise. Two conductor stranded coaxial cables, 24 inches long, connected the electrodes to the inputs of the amplifiers. Their shields were grounded to reduce noise.

Amplifier outputs were connected to a threshold detection circuit via 47 KΩ resistors. Originally, the purpose of the threshold detector was to inform the computer that the EMG signal strength was above a certain level so that computer sampling could begin. The threshold level was arbitrarily chosen so that a logic low (active) pulse occurred when the muscles began to contract. The result of this would have been computer modeling of a transient EMG signal. It was decided that static contractions could be more accurately modeled than dynamic contractions even though dynamic contractions are more realistic. Although not used in these experiments the trigger circuitry was retained since it could be used with no modification as a noise threshold preventing accidental actuation of a prosthetic system.

A Commodore PET 2001 Graphics Series computer, manufactured by Commodore Business Machines, Inc., Santa Clara, CA., along with a Commodore Model 8030 dual floppy disk drive was used for analysis and storage of the EMG signals. A Commodore 4022 dot matrix printer was also connected to the PET. Communication and transmission of data to and from the PET was done on the IEEE-488 general purpose interface bus (GPIB) located on the back of the computer.

Amp 1 and amp 2 were alternately sampled by the PET computer at a sampling frequency of 5000 Hz. This was accomplish by routing the amplifier outputs to two of the inputs, A and B, on a quad-analog IC switch, shown in Figure 3. The outputs of both switches were connected together, however only one switch was asserted at a given time since the control signal for switch B was the complement of the control signal for switch A. The PET IEEE data valid (DAV) line was switched from logic low to high to low by machine language software 5000 times per second during data acquisition. When the line was low switch B was on and output from amp 2 was sampled, and vice versa for amp 1 when the DAV line was high. Settling time for the switches was 60 nS so the switching rate of 10 KHz presented no problems. The output connected to channel 2 of a digital storage oscilloscope Model OS1420, Gould, Inc., Hainaut, Essex, England. The storage oscilloscope permitted visual analysis of the un-digitized EMG signal from either amplifier.

The signal then went to the 0804 ADC V_{in}^{+} input. A detailed schematic of the 0804 ADC circuitry is shown in Appendix A. The 0804 was chosen for its low power requirements, self containment, and TTL compatiblility. Input voltage was adjusted to a ±5 V range. The A/D conversion rate was chosen high enough so there would be no aliasing problems when the digital signal was sampled by the computer. The digitized 8-bit signal was latched on the tri-state output buffer when the $\overline{RD}$ pin was driven low (asserted) by the PET IEEE NRFD line. When $\overline{RD}$ was high the 8-bit output of the A/D converter floated permitting use of the IEEE-488 data lines for other operations. Power supply for the 0804 ADC was provided by a five volt IC regulator connected to the +9 V source. The five volt source also powered the inverter chip connected to the control signal for the analog IC switch.

A 1408 D/A converter chip was connected to the IEEE BUS permitting visual analysis of the digitized signal. It operated in a free running mode. Its analog output was amplified and sent to channel 1 of the digital oscilloscope to permit comparison to the un-digitized signal. Either channel could be plotted on a model 7004B X-Y recorder, Hewlett-Packard, Inc., Fort Collins, CO., to obtain a hard copy record of the oscilloscope display.

Description of Software

Data acquistion was performed in real time. Therefore, a machine language subroutine was required for sampling the data. Appendix C1 includes a printout of the data acquistion programs called "MAIN" and "MACH."

MAIN was written in PET BASIC and is the main program. It calls the 6502 machine language program "MACH". MAIN was written in a structured modular form. A main menu with submenus gave the operator several options. One could enter the ID of the participating subject, take a sample, review a stored sample on the oscilloscope, or get a directory of the data disk. If the operator chose to take a sample he could pick any of the six motions or return to the main menu. After the sample was taken he could review the signal from either electrode, store the sample on disk, retake the sample, or return to the motion menu. Once a sample was stored on disk one need not enter the name for a new sample each time. The sample number was automatically incremented for the last motion chosen. Names of the data files were of the form IIIAMMM.E.SN, where III was the initials of the subject, A was C or T for calibration data or test data respectively, MMM was a three letter abbreviation of the associated motion, E was a 1 or 2 denoting electrode 1 or electrode 2 respectively, and SN was the sample number. These descriptive names made it easy to search and retrieve the files for later analysis.

Before MACH was called, the IEEE NRFD line was asserted low turning on the 0804 ADC. The machine language subroutine MACH waited for a low pulse on the IEEE NDAC line signifying the start of a contraction, but that section of the program was not used when only static contractions were considered. It was initially intended that the two electrodes would be sampled as close in time as possible, however, this resulted in erroneous readings because the IEEE DAV line could not change signs fast enough to permit sampling of the second electrode. This problem was alleviated by placing exactly half of the timing loop after sampling electrode 1 and the other half after sampling electrode 2. Fisher and Jensen (1980) provided example real-time machine language sampling programs which aided in the design of MACH. Five hundred twelve data points per electrode were stored in memory, but only the first 200 or 300 were stored on disk. Program execution returned to the main program and the ADC was shut off after data sampling was complete.

Experimental Methods

A brace was built that firmly held the subject's arm in place so that only static contractions occurred. The forearm was placed on a padded arm rest and the hand was secured to a dowel by an elastic band. In all cases the right arm provided the EMG signals. The subject was comfortably seated at a laboratory bench with the right elbow bent at approximately 90°. The different motions could have been sampled in any order but were chosen to reduce fatigue. The order was hand grasp, wrist flexion, supination, and extension, hand splay, and wrist pronation. There was no previous training by the subjects to help them reproduce the limb motions more consistantly. This may have caused a larger in-class variance for the calibration data set.

Subjects repeated the six motions 14 times for the calibration set. They were asked to contract their muscles with "medium" intensity. This was a subjective measure but could be improved with training.

A problem with the system was the time period required for data storage. It took about 40 seconds to store 1024 data points on disk. This made calibration sessions excessively long. The length of the test sessions was considerably reduced because only 400 points, 200 per electrode, were stored on disk.

DATA ANALYSIS SOFTWARE

Variance and Zero Crossings

Printouts of the variance and zero crossing algorithms are in Appendix C2. Variance is defined as

$$\sigma^2 = \frac{N\sum_{i=1}^{N} X_i^2 - (\sum_{i=1}^{N} X_i)^2}{N(N-1)} \quad .$$

Zero crossings are the number of times the signal changes sign per sampling period. Variance and zero crossings were determined off-line with files retrieved much the same way they were stored. Two hundred data points were used in the calculation of variance while zero crossings were determined using 300 data points. Since only 200 points were sampled in the test data sets one would expect 1/3 fewer zero crossings. This was confirmed by experimentation so the decision planes in the feature space of variance and zero crossings were adjusted to accommodate the test samples. As long as 200 data points were used in the test data files the variance and zero crossing decision planes are valid. Appendix B lists values of zero crossings and variances for the calibration data sets. Figures 4 and 5 show the plots of these values for electrode 1 and electrode 2 respectively.

Decision planes were drawn separating groups of motions by visual inspection of the feature space. These decision planes can be found in Figures 4 and 5. Not all possible decision planes apparent to the eye are included. Only decision planes that made up the final discrimination criteria are included in Figures 4 and 5. They were optimized based on the first set of test data.

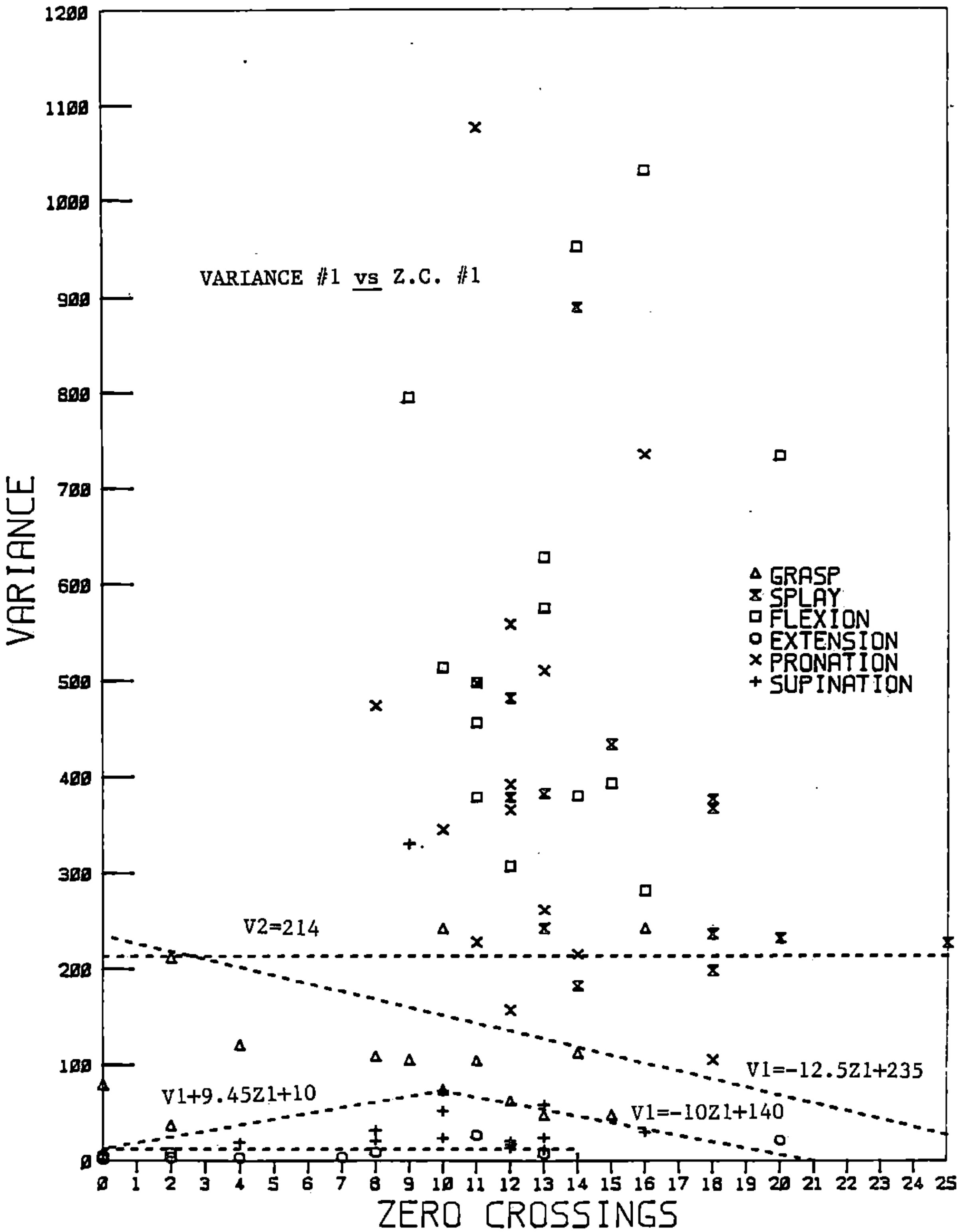

Figure 4 Electrode #1 decision planes in the feature space of variance and zero crossings. Zero crossings are based on 300 data points per sample. Decision planes are adjusted to 200 data points per sample. Variance is in arbitrary digitizer units.

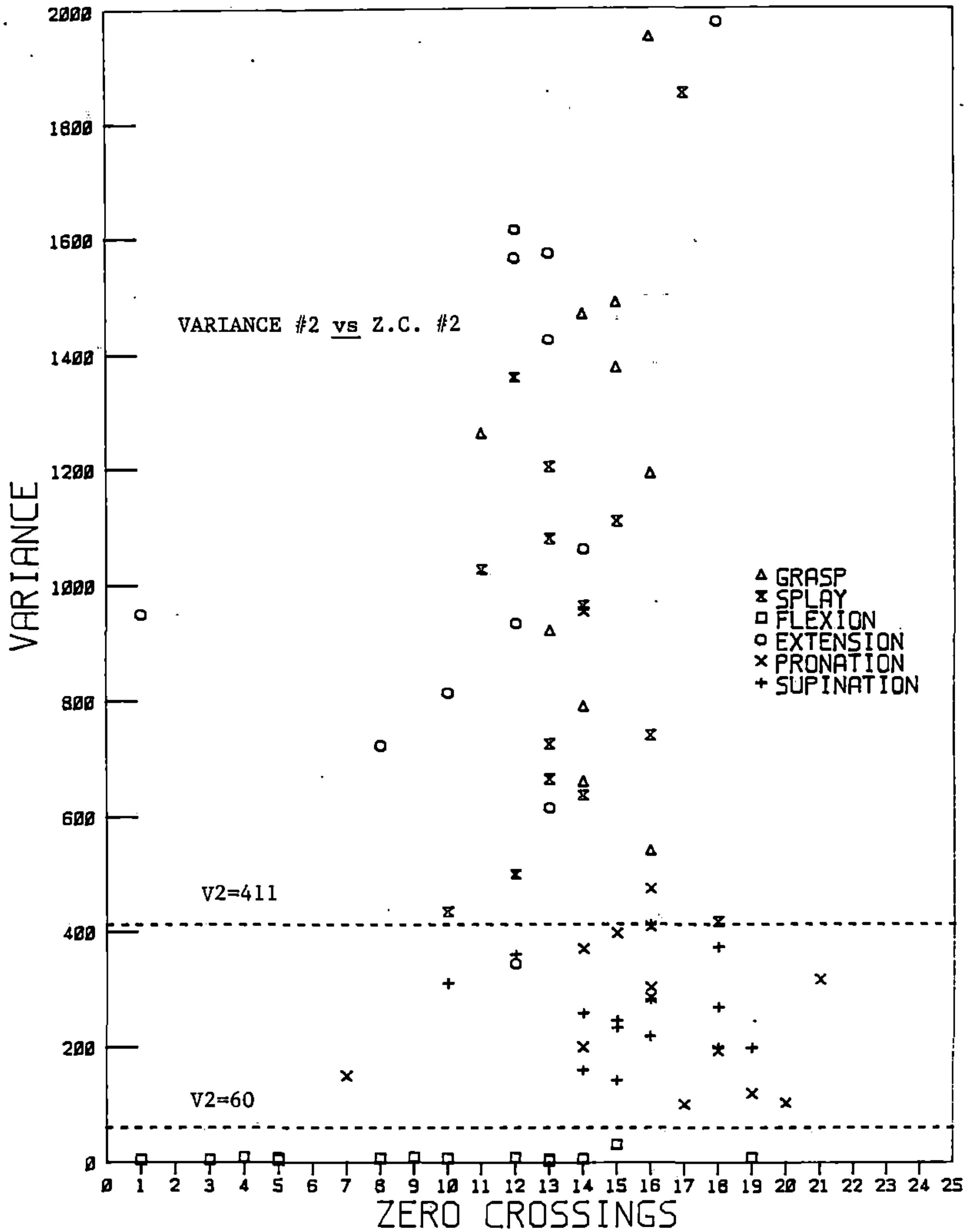

Figure 5 Electrode #2 decision planes in the feature space of variance and zero crossings. Zero crossings are based on 300 data points per sample. Decision planes are adjusted to 200 data points per sample. Variance is in arbitrary digitizer units.

Autoregressive Modeling

A linear AR model of the two EMG signals was developed for motion discrimination. As in the work of Graupe et al. (1978), Graupe and Salahi (1979), Graupe et al. (1982), and Doerschuk et al. (1979,1983) an AR model can be considered valid because signal stationarity is assumed when the sampling window is .05 seconds or less. At a sampling rate of 5000 Hz AR coefficients were determined from 250 data points. This resulted in a .05 second time window.

AR coefficients were estimated by employing a least-squares algorithm, called "ARM", which is shown in Appendix C2. It was decided that creating a a least-squares program for the PET computer would be easier than developing the software necesary to transfer the thousands of pieces of data to another computer that already had the appropriate least-squares algorithm.

The prediction error from Equation 3 can be represented by

$$E(A) = \sum_{t=p+1}^{n} [y_t - (A_0 + A_1X_{1t} \quad +\ldots)]$$

where E is a function of the AR coefficients, and X_{1t} is the same as y(t-i). Reduced and put in matrix form this is (Singh and Titli, 1978)

$$E(A) = (Y-XA)'(Y-XA) \qquad (5)$$

where Y is a n x 1 matrix, A is a p+1 x 1 matrix, and X is a n x p+1 matrix. The single apostrophe means the first matrix in parentheses is transposed. For least squares error the derivative of E(A) with respect to A must be zero. Taking the derivative of Equation 5 and setting it equal to zero yields $0 = X'Y - X'XA$. Solving for A gives $A = (X'X)^{-1}X'Y$.

The program "ARM" retrieves from disk one calibration data set at a time and calculates X'X, a p+1 x p+1 matrix and X'Y a p+1 x 1 matrix. Any order model could be specified, however, computation time for orders greater than four was very long because the program was written in BASIC, thus the final models were fourth order. After X'X was determined it had to be inverted. This was possible by applying a FORTRAN matrix inversion program given by Hornbeck (1975). It was converted to PET BASIC and modified for this particular application. This was the most time consuming section of the program. Finally $(X'X)^{-1}X'Y$ was computed.

This program was tested and verified using data with known AR coefficients determined by a statistical software package on the WILBUR program at the Iowa State University Computation Center. The data consisted of 100 points and was represented by a fourth order model. The PET BASIC program produced AR coefficients nearly identical to those of the WILBUR program. Differences were probably due to round-off error.

Averaged models of the fourteen samples per motion per electrode were used in the final motion discrimination models. Since there was no previous training by the subjects some of the calibration samples had variances and zero crossings that were much larger or smaller than the average for any particular motion. If a sample had a variance more than three times or less than 1/3 the average variance of the 14 samples for a particular motion, then it was considered ill-fitting data and its corresponding AR coefficients were not included in the averaged AR model.

RESULTS and DISCUSSION

To test the identification accuracy of the decision planes and the AR models 10 new samples per motion were taken. Each sample contained two hundred data points. Again subjects contracted their arms at medium intensity. Testing was accomplished off-line, necessary so that the same data used to test the variance and zero crossing decision planes could be used to test the AR models and a combination of both.

During discrimination it was assumed that one of the six posible motions was occurring. In an actual artificial arm application a threshold detector could prevent constant prosthesis movement since the on-board computer assumes one of the six motions is occurring, or the state of 'rest' or 'hold' could be a seventh function. This seventh function would have parameters in the feature space of variance and zero crossings and its own AR coefficients. Since one of six motions is assumed to exist, the motions with the best inter-class separability were identified first. If a sample did not fit the criteria for the first motion, it was assumed to be one of the remaining five motions. For example, if the motion was not identified as one of the first five motions it was identified as the sixth motion by default. It should be noted that there is a 16.7% chance of randomly choosing the correct answer.

Based on the results from the first test data set, the decision planes were modified to improve dicrimination accuracy. Then another new set of test data was obtained and it was from these samples that final discrimination results were obtained. There were 10 samples per motion at medium intensity contraction. These results are not biased and can be considered worst case accuracy of the system. Doerschuk et al. (1983) are the only authors cited who state that a completely new set of data was used to test their models.

The decision criteria used in discrimination, based on only variance and zero crossings, are as follows.

If V2<60 then Flexion

If (V1<12)AND(Z1<14) then Extension

If (V1<9.45*Z1+10)AND(V1<-10*Z1+140) then Supination

If (V2>411)AND(V1>-12.5*Z1+235) then Splay

If V1<-12.5*Z1+235 then Grasp

The remainder is Pronation

V1, V2, Z1, and Z2 are variances and zero crossings from electrode 1 and electrode 2 respectively. These criteria resulted in a 63.3% correct identification of the second test data set.

A digitized EMG signal consisting of 200 points is shown in Figure 6. The signal is from electrode 1 during wrist flexion. The middle plot is the residual error, described by Equation 4, resulting from the flexion AR model. The computer correctly identified the motion of this sample as flexion. The bottom plot shows the residual error using the input signal and the AR model for wrist extension. Clearly, it is not a good fit and was not chosen by the computer.

The AR models were tested with the first test data set with the same assumption that one of the six motions is occurring. Models based on averages of all 14 samples per motion and models based on averages excluding the samples with ill-fitting data were tested.

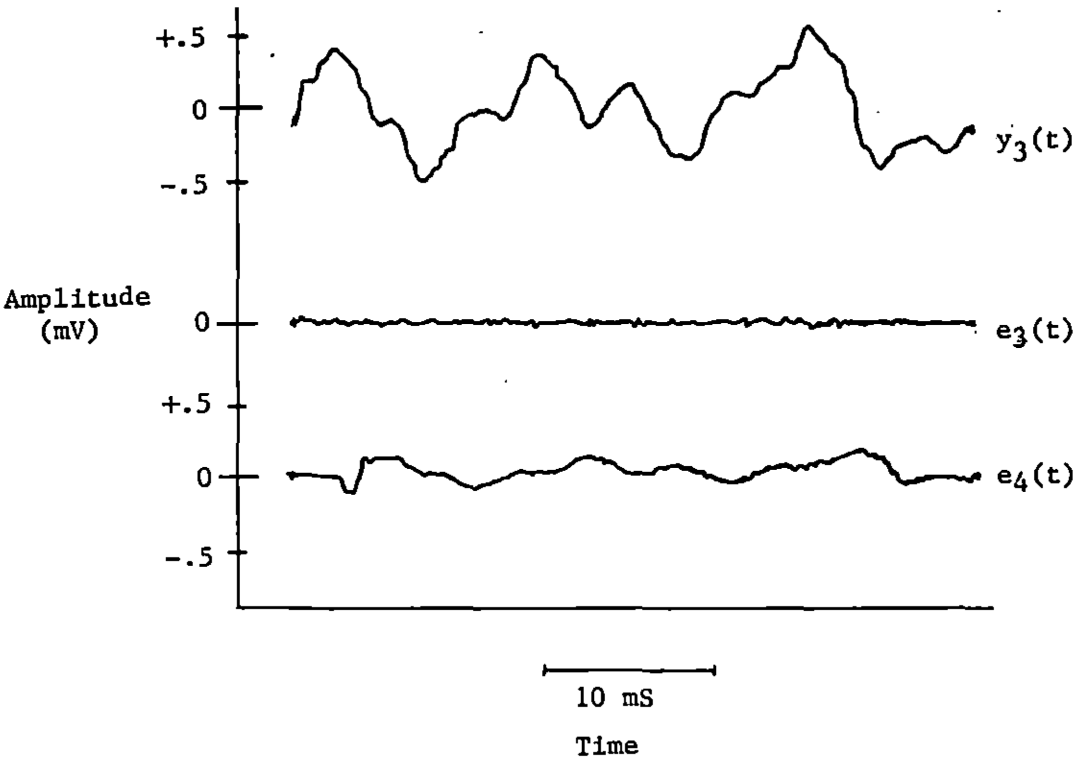

Figure 6 The top plot shows the EMG signal from electrode #1 during flexion. The other two plots are the residual error, Equation 4, from two different models. The middle plot is the error of the flexion model and the lower plot is the error of the extension model as compared to the first plot.

Accuracy (correct motion identification) of the models with outlier data removed was 6.4% higher than with the data intact. The best accuracy obtained by basing discrimination solely on the AR coefficients was only 37.5%. This includes tests of models from both electrodes (which were independent of each other). Electrode 1 (digital flexor) models correctly identified motions 45.4% of the time and electrode 2 (digital extensor) models identified correctly 29.8% of the time. Some motions were more identifiable than others. Flexion and supination models showed the best accuracy, however, correct identificaton of these two motions based on variance and zero crossing was greater than when based on AR modeling.

Although the wrong motion was chosen many times for a particular input signal it was consistently wrong. For example, when the actual motion was grasp the computer often chose pronation based on the models from electrode 1. This fact was used to advantage. In the final decision criteria logical combinations of motion choices from one electrode or from both were incorporated with decision planes from variance and zero crossings.

The best results were obtained with a combination of decision planes in the variance/zero crossing space and AR modeling. Since feature space of variance and zero crossings contain more discrimination information than AR coefficients it was the primary discrimination criterion. Sukhan and Saridis (1982) also found variance and zero crossings to contain more discrimination information.

The final decision criteria are,

If V2<60 then Flexion

If (V1<12)AND(Z1<14) then Extension

If (V1<9.45*Z1+10)AND(V1<-10*Z1+140) then Supination

If ((V2>411)AND(E1=PRONATION)AND(V1<-12.5*Z1+235))OR(E1=FLEXION) then Splay

If ((E1=PRONATION)AND(E2=PRONATION))OR(E1=GRASP)OR(E1=SPLAY) then Pronation

If (E1=EXTENSION)OR((E1=PRONATION)AND(V1<214)) then Grasp

Remainder is Pronation

V1 ,V2, Z1, and Z2 are as before. E1 and E2 are the best fitting AR models based on electrode 1 and electrode 2 respectively. It was seen from the results using the first test data set that the most difficult motion to discriminate is pronation, for both the decision planes and the AR models. Consequently, any samples not fitting one of the first six decision criterion are assumed to be pronation. Graupe et al. (1982) also experienced difficulty in discriminating pronation. They employed cross correlation relationships between two electrodes in their design. Coincidently, pronation was the only motion that could be consistently identified based on cross correlation.

The second test data set resulted in a worst case accuracy of 71.7%. When the first test data set was used discrimination accuracy was 91%, however, this is biased since it was used to modify the decision criteria.

It should be noted that no formal training was involved in either the calibration data or the test data. After supplying the calibration and test data the primary subject was able to more consistently reproduce the six motions with medium contraction. It is not certain what effect, if any, this had on the final results, but if new data were recorded for calibration purposes it is possible that more representative decision planes and AR coefficients would result.

The final decision criterion was also tested with maximal contracton motions to test its flexibility under varying conditions. An accuracy of 53.8% was obtained. This is most likely due to the good discriminability of flexion and extension.

SUMMARY

Variance, zero crossings, and auto regressive modeling of EMG signals in the lower arm were used for discrimination of six motions in the lower arm. These motions were hand grasp and splay, wrist flexion and extenison, and wrist pronation and supination. EMG signals were obtained via two high input impedance differential amplifiers and stored on a magnetic disk for off-line analysis. Variance/zero crossing decision planes, and AR coefficients were determined and tested with a separate set of test data.

Variance, zero crossings, and AR modeling of EMG signals provide information which permits discrimination of lower arm motion at rates significantly greater than random chance. Variance and zero crossings provide more discrimination information than AR modeling.

Although the results at this time are inadequate for prosthesis control, there is much promise and room for improvement. Through standardization of motions during the calibration phase, decision criteria that relate EMG signals to known forces might be obtained. This would reduce some of the subjectiveness of contracting the muscles with "medium" intensity, as perceived by the subject.

Training could be facilitated if a dedicated computer determined (on-line and with little delay) the motion based on the subject's EMG signals. This would provide the subject with instant feedback, aiding in more consistant contractions.

Proportional control algorithms may be implemented for prosthesis control, however, computation time would increase due to more motion

conditions that would have to be discriminated. Combined with learning algorithms AR correlation may cause motion discrimination to be too slow. Since variance and zero crossings provide more discrimination information and require less computation time than AR modeling, they seem to be the most promising EMG parameters for future upper limb prosthesis control.

Prosthesis control systems should be designed to require as little training by the amputee as possible, however, similar to someone relearning to use an injured limb, some degree of training by the amputee will likely be necessary. Just as human training would improve prosthesis performance so would prosthesis training. That is, a prosthesis that "learns" to respond to the EMG signals that are most naturally produced by the amputee might become more acceptable to the amputee.

No matter how technical and objective the testing of a prosthesis control system is, the final measure is a subjective evaluation by the amputee. Many amputees who own a myoelectric prosthesis rarely wear them. When they do wear them it is usually not for functional reasons but cosmetic reasons (Shannon, 1979b). Cosmetically adequate prostheses should be designed with natural and effective control systems mated to natural and effective feedback systems if patient acceptability is to be achieved.

ACKNOWLEDGEMENTS

Experimental procedures in this research were designed to ease any discomfort or fatigue to the subjects during data acquistion. This research was approved by the Human Subjects Committee at Iowa State University. Each participating subject signed two copies of a consent form which stated exactly what the research entails, what possible pain or discomfort he or she can expect, and that he or she understands it and willfully volunteers to particpate in the research.

I wish to express my appreciation and thanks to Dr. William H. Brockman for his help in this research and in my academic growth. Special thanks go to Bear for being a constant source of motivation, and for helping in the typing of this paper. Above all, I want to thank my parents for all their support and encouragement these last 25 years, and to whom this work is dedicated.

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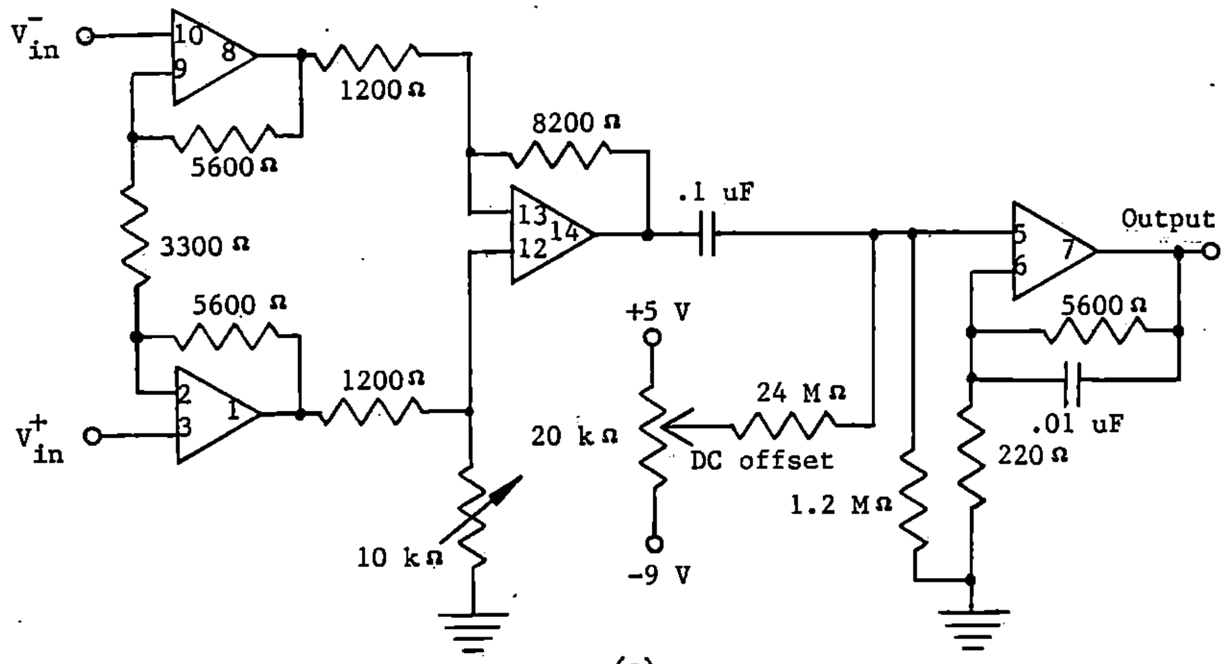
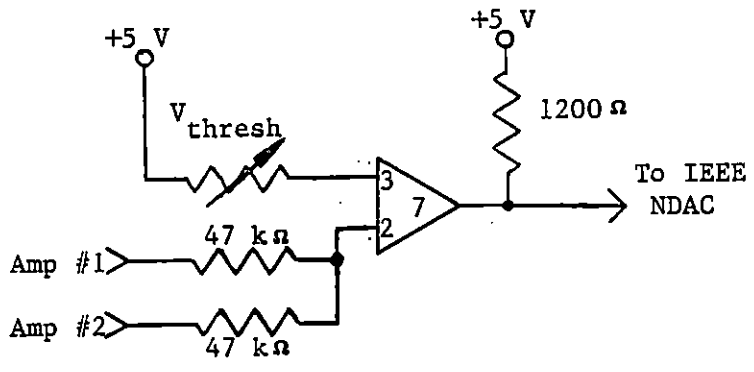
APPENDIX A



(a)



(b)

Figure A. Both differential EMG amplifiers were of the design in (a). All four sub-amplifiers are FET Op Amps with $10^{12}\Omega$ input impedance. Numbers inside the triangles represent pin numbers on a single quad Bi-FET Op Amp. Figure A(b) is the EMG threshold circuit. V_{thresh} can be varied by adjusting the potentiometer.

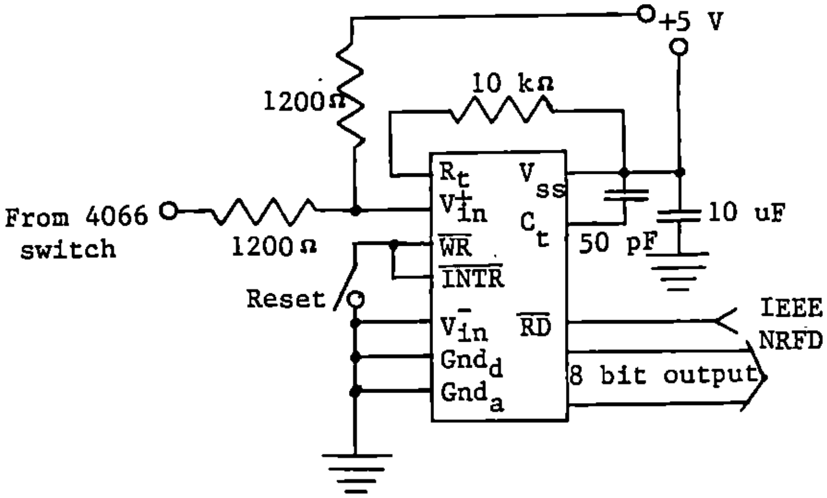


Figure A(c). The 0804 National Semiconductor A/D converter is shown. With C_t =50 pF and R_t =10 kΩ the A/D conversion rate is approximately 1M Hz. $\overline{\text{INTR}}$ is connected directly to $\overline{\text{WR}}$ making the ADC free running. The two 1200Ω resisters allow for a ±5 V input which corresponds to the maximum voltage output expected from the differential EMG amplifiers.

APPENDIX B

Variances of the fourteen samples for each of the six samples and two electrodes are shown below. These are the data points represented in figures four and five. Values with a "*" in front of them were not close to the average for that motion and those corresponding data points were not included in the estimation of the AR models.

ELECTRODE #1

GRASP	SPLAY	FLEXION	EXTENSION	PRONATION	SUPINATION
242.087	377.75	456.232	1.5561889	391.755553	10.6912812
242.311	* 1303.2	380.122	3.8793969	558.168618	72.8115578
62.4452	182.21	575.168	2.9020100	355.272261	31.9326382
210.617	888.60	1030.73	5.3712311	496.672337	57.6566834
36.4840	432.95	392.899	7.3463316	510.760819	23.7965829
46.4840	226.55	498.278	3.8965326	735.252236	23.678794
46.7963	376.24	387.117	*21.153668	176.131432	12.6865327
73.6121	366.25	795.041	3.0516582	156.771633	51.7298452
103.985	381.62	281.128	3.0150753	105.199774	22.1664022
112.234	242.28	514.272	4.0964572	258.933141	38.0477087
104.675	236.14	732.592	*26.767437	474.331658	15.606407
120.249	198.51	378.984	*90.415050	215.854845	10.5608015
108.937	480.67	952.543	1.5446984	345.233256	21.0398955
79.0934	232.74	627.587	8.1543712	227.680754	*336.170754

ELECTRODE #2

GRASP	SPLAY	FLEXION	EXTENSION	PRONATION	SUPINATION
1350.62	725.39	3.18954	1425.7276	317.53407	230.537538
789.504	1852.8	5.77886	2229.5867	150.452385	412.797598
1377.66	498.82	7.77324	933.25376	133.921583	350.804799
2537.25	1110.1	*30.7959	1062.6421	395.571583	246.315859
540.843	416.59	5.33565	1976.9345	*554.309322	160.130055
2614.56	665.35	5.62288	*344.56874	487.633769	279.264095
1192.92	535.59	8.85354	1565.9880	220.431935	140.013953
1469.67	1079.8	7.26870	814.01947	*182.652035	218.312609
921.570	433.45	3.80044	614.64713	122.235578	159.391332
1439.69	1027.1	9.77766	*34984024	*180.253369	271.540643
1262.81	1360.0	4.59256	3100.9054	303.779274	220.761286
2747.82	965.40	7.08218	1610.4938	285.330528	199.01031
668.245	739.97	3.80643	722.04110	474.432203	312.135433
2770.68	1284.1	8.59889	1573.3275	370.639427	258.785823

Shown are the zero crossings for the calibration data. They are based on 300 hundred data points and are the abscissa values in figures four and five.

ELECTRODE #1

GRASP	SPLAY	FLEXION	EXTENSION	PRONATION	SUPINATION
16	12	11	0	12	4
10	10	14	2	12	10
12	14	13	4	12	8
2	14	16	0	11	13
2	15	15	13	13	13
13	25	11	7	16	10
15	18	12	20	11	12
10	18	9	0	12	10
11	13	16	2	18	12
14	13	10	0	13	16
9	18	20	11	8	12
4	18	11	8	14	13
8	12	14	0	10	8
0	20	13	2	11	9

ELECTRODE #2

GRASP	SPLAY	FLEXION	EXTENSION	PRONATION	SUPINATION
16	13	13	13	21	15
14	17	14	11	7	16
15	12	12	12	18	12
12	15	15	14	15	15
16	18	3	18	14	14
18	13	13	12	16	18
16	14	9	12	14	15
14	13	10	10	17	16
13	10	5	13	19	19
15	11	5	1	20	18
11	12	1	10	16	16
17	14	8	12	16	18
14	16	19	8	16	10
19	13	4	13	14	14

APPENDIX C1

The main program "MAIN" is shown below. Successive 'REM' statements separate the modular units for easy identification. The program includes error checking and is 'menu' oriented.

```
10 SN=0
15 N=299
20 I1=PEEK(59425):I2=PEEK(59427):I3=PEEK(59456):REM STORE INITIAL VALUES
30 POKE 52,255:POKE 53,79 :REM REDEFINE TOP OF MEMORY
40 POKE59456,PEEK(59456)AND251: REM ATN ON
50 POKE59426,85:POKE59426,63 : REM UNL & UNT
60 POKE59456,PEEK(59456)OR4 : REM ATN OFF
65 POKE59426,255:REM CLEAR DATA LINES
70 REM
80 PRINT"□":PRINT:PRINT:PRINT"          *** MAIN MENU ***":PRINT:PRINT:PRINT
90 PRINT"1.  ENTER ID":PRINT:PRINT"2.  TAKE A SAMPLE"
100 PRINT:PRINT"3.  CATALOG DATA DISK":PRINT:PRINT"4.  REVIEW A SAMPLE ON DISK"
105 PRINT:PRINT"5.  QUIT":PRINT:PRINT
110 GET Q$:IF Q$="" THEN 110
115 Q%=VAL(Q$):ON Q% GOTO 130,200,1000,1300,1100
120 GOTO 80
130 PRINT:INPUT" ENTER INITIALS, AND SAMPLE # OF SUBJECT";ID$,SN$
135 PRINT:INPUT"ENTER NUMBER OF SAMPLE PTS.";N:N=N-1
140 SN=VAL(SN$): REM INITIALIZE REAL VARIABLE SN
150 GOTO 80
160 REM
170 REM SAMPLE MENU
180 REM
200 PRINT"□":PRINT:PRINT"WHICH MOTION DO YOU WANT  TO SAMPLE?"
210 PRINT:PRINT"1.  HAND GRASP":PRINT"2.  HAND SPLAY":PRINT"3.  WRIST FLEX"
220 PRINT"4.  WRIST EXTEND":PRINT"5.  WRIST PRONATE":PRINT"6.  WRIST SUPINATE"
230 PRINT"7.  RETURN TO MAIN MENU":PRINT:PRINT
235 GET MO$:IF MO$="" THEN 235
240 MO%=VAL(MO$):ON MO% GOTO 250,260,270,280,290,300,80
250 MO$="GRA":GOTO 400
260 MO$="SPL":GOTO 400
270 MO$="FLX":GOTO 400
280 MO$="EXT":GOTO 400
290 MO$="PRO":GOTO 400
300 MO$="SUP"
310 REM
320 REM
330 REM
400 PRINT"TURN AMPLIFIER ON AND RESTART IT,THEN":PRINT
402 PRINT"PRESS ANY KEY TO TAKE A SAMPLE"
405 POKE59426,255:REM CLEAR DATA LINES
410 GET Q$: IF Q$="" THEN GOTO 410
415 IF Q$="Z" THEN GOTO 80:REM PANIC BUTTON
420 POKE59456,PEEK(59456)AND253: REM NRFD ON (0804 ON)
430 SYS 20480: REM MACHINE SUBROUTINE
440 POKE59456,PEEK(59456)OR2: REM NRFD OFF (0804 OFF)
450 POKE59425,I1:POKE59427,I2:POKE59456,I3:REM RESTORE INITIAL VALUES
460 N1$=ID$+MO$+".1."+SN$:N2$=ID$+MO$+".2."+SN$
470 REM
490 REM
500 PRINT"□":PRINT:PRINT"1.  REVIEW "N1$:PRINT"2.  REVIEW "N2$
510 PRINT"3.  SAVE "N1$" AND "N2$:PRINT"4.  RETAKE LAST SAMPLE"
520 PRINT"5.  RETURN TO  MOTION MENU":PRINT:PRINT
525 GET Q$:IF Q$=""THEN 525
```

```
530 Q%=VAL(Q$):ON Q% GOTO 540,580,620,400,200
540 FOR I=0 TO N
550 POKE 59426,PEEK(20736+I)
560 NEXT
570 GOTO 500
580 FOR I=0 TO N
590 POKE 59426,PEEK(21248+I)
600 NEXT
610 GOTO 500
620 PRINT:PRINT:PRINT:PRINT"IS AMPLIFIER TURNED OFF?"
630 GET Q$:IF Q$="" THEN 630
640 SCRATCH D1,(N1$):SCRATCH D1,(N2$):REM SCRATCH IF FILE ALREADY EXISTS
650 DOPEN#2,(N1$),D1,W
660 GOSUB 1200:REM CHECK TO MAKE SURE FILE OPENED OK
670 FOR I=0 TO N
680 :PRINT#2,PEEK(20736+I)
690 :NEXT
700 DCLOSE:GOSUB 1200:REM MAKE SURE FILE CLOSED OK
710 DOPEN#2,(N2$),D1,W
720 GOSUB 1200:REM MAKE SURE FILE OPENED OK
730 FOR I=0 TO N
740 :PRINT#2,PEEK(21248+I)
750 :NEXT
760 DCLOSE: GOSUB 1200:REM MAKE SURE FILE CLOSED OK
780 SN=SN+1:REM INCREMENT SAMPLE NUMBER
790 SN$=RIGHT$(STR$(SN),LEN(STR$(SN))-1):GOTO 200
800 REM
810 REM
820 REM
1000 PRINT:PRINT"IS AMPLIFIER TURNED OFF"
1002 GET Q$:IF Q$="" THEN 1002
1005 PRINT:PRINT:CATALOG D1:PRINT:PRINT
1007 PRINT"PRESS <RTN> TO RETURN TO MAIN MENU"
1010 GET Q$:IF Q$="" THEN GOTO 1010
1020 GOTO 80
1030 REM
1040 REM
1045 POKE59425,I1:POKE59427,I2:POKE59456,I3:REM RESTORE INITIAL VALUES
1100 PRINT"THANK YOU!":END
1110 REM
1120 REM
1200 IF DS>1 THEN PRINT DS$:END
1210 RETURN
1220 REM
1230 REM
1240 REM
1300 PRINT:PRINT:PRINT"IS AMPLIFIER TURNED OFF?"
1310 PRINT:PRINT"ENTER FILE NAME(IIIMMM.X.SN)":PRINT
1315 INPUT NN$
1320 DOPEN#2,(NN$),D1:REM OPEN FILE
1330 GOSUB 1200:REM MAKE SURE FILE OPENED OK
1340 FOR I=0 TO N
1350 :INPUT#2,NN:POKE (20736+I),NN
1360 NEXT
1362 DCLOSE:GOSUB 1200
1365 PRINT: PRINT"TURN ON AMPLFIER."
1367 GET Q$:IF Q$="" THEN 1367
1370 FOR I=0 TO N
1380 :POKE 59426,PEEK(20736+I)
1390 NEXT
1410 GOTO 80
```

This is the machine language program "MACH". Five hundred twelve bytes of data are stored starting in location $5100. The 'NOP' statements are stricktly for timing purposes. MAIN branches to 5000 HEX and execution begins.

```
5000 78       SEI
5001 A2 00    LDX #$00
5003 AD 40 E8 LDA $E840
5006 29 01    AND #$01
5008 D0 F9    BNE $5003
500A A9 08    LDA #$08
500C 0D 23 E8 ORA $E823
500F 8D 23 E8 STA $E823
5012 A9 08    LDA #$08
5014 8D 00 55 STA $5500
5017 CE 00 55 DEC $5500
501A D0 FB    BNE $5017
501C AD 20 E8 LDA $E820
501F 9D 00 51 STA $5100,X
5022 A9 F7    LDA #$F7
5024 2D 23 E8 AND $E823
5027 8D 23 E8 STA $E823
502A EA       NOP
502B EA       NOP
502C EA       NOP
502D A9 08    LDA #$08
502F 8D 00 55 STA $5500
5032 CE 00 55 DEC $5500
5035 D0 FB    BNE $5032
5037 AD 20 E8 LDA $E820
503A 9D 00 53 STA $5300,X
503D E8       INX
503E D0 CA    BNE $500A
5040 A9 08    LDA #$08
5042 0D 23 E8 ORA $E823
5045 8D 23 E8 STA $E823
5048 A9 08    LDA #$08
504A 8D 00 55 STA $5500
504D CE 00 55 DEC $5500
5050 D0 FB    BNE $504D
5052 AD 20 E8 LDA $E820
5055 9D 00 52 STA $5200,X
5058 A9 F7    LDA #$F7
505A 2D 23 E8 AND $E823
505D 8D 23 E8 STA $E823
5060 EA       NOP
5061 EA       NOP
5062 EA       NOP
5063 A9 08    LDA #$08
5065 8D 00 55 STA $5500
5068 CE 00 55 DEC $5500
506B D0 FB    BNE $5068
506D AD 20 E8 LDA $E820
5070 9D 00 54 STA $5400,X
5073 E8       INX
5074 D0 CA    BNE $5040
5076 58       CLI
5077 60       RTS
5078 00       BRK
```

APPENDIX C2

Variance was calculated off-line using the program below.

```
10 DIM VAR(5,1,13)
20 INPUT"ENTER INITIALS AND NUMBER OF SAMPLE PTS.";ID$,N
30 FOR MO=1 TO 6: ON MO GOTO 40,50,60,70,80,90
40 :MO$="GRA":GOTO 100
50 :MO$="SPL":GOTO 100
60 :MO$="FLX":GOTO 100
70 :MO$="EXT":GOTO 100
80 :MO$="PRO":GOTO 100
90 :MO$="SUP"
100 :FOR SN=1 TO 14
110 ::SN$=RIGHT$(STR$(SN),LEN(STR$(SN))-1)
120 ::N1$=ID$+MO$+".1."+SN$:N2$=ID$+MO$+".2."+SN$
130 ::X1=0:X2=0
140 ::DOPEN#2,(N1$),D1:IF DS>1 THEN PRINT DS$;:V=V+1:PRINT V:GOTO 190
150 ::FOR I=0 TO N-1
160 :::INPUT#2,Y:IF DS>1 THEN PRINT DS$;:V=V+1:PRINT V
170 :::X1=X1+Y:X2=X2+Y*Y
180 ::NEXT I
190 ::DCLOSE
200 ::VAR(MO-1,0,SN-1)=(N*X2-X1*X1)/(N*(N-1))
210 ::X1=0:X2=0
220 ::DOPEN#2,(N2$),D1:IF DS>1 THEN PRINT DS$;:V=V+1:PRINT V:GOTO 270
230 ::FOR I=0 TO N-1
240 :::INPUT#2,Y:IF DS>1 THEN PRINT DS$;:V=V+1:PRINT V
250 :::X1=X1+Y:X2=X2+Y*Y
260 ::NEXT I
270 ::DCLOSE
280 ::VAR(MO-1,1,SN-1)=(N*X2-X1*X1)/(N*(N-1))
290 :NEXT SN
300 NEXT MO
310 OPEN 4,4:CMD4
320 PRINT:PRINTTAB(32)"ELECTRODE #1":PRINT
330 PRINT"SAMPLE  GRASP        SPLAY        FLEXION      EXTENSION    PRONATION";
340 PRINT"   SUPINATION"
350 PRINT"______  _____        _____        _______      _________    _________";
360 PRINT"   __________"
370 FOR I=0 TO 13
380 :PRINT" "I+1;:LL=5-LEN(STR$(I+1))
390 :FOR J=0 TO 5
400 ::PRINTSPC(LL)VAR(J,0,I);
410 ::LL=11-LEN(STR$(VAR(J,0,I)))
420 :NEXT
430 :PRINT
440 NEXT
450 PRINT:PRINT:PRINTTAB(32)"ELECTRODE #2":PRINT
460 PRINT"SAMPLE  GRASP        SPLAY        FLEXION      EXTENSION    PRONATION";
470 PRINT"   SUPINATION"
480 PRINT"______  _____        _____        _______      _________    _________";
490 PRINT"   __________"
500 FOR I=0 TO 13
510 :PRINT" "I+1;:LL=5-LEN(STR$(I+1))
520 :FOR J=0 TO 5
530 ::PRINTSPC(LL)VAR(J,1,I);
540 ::LL=11-LEN(STR$(VAR(J,1,I)))
550 :NEXT
560 :PRINT
570 NEXT
580 PRINT#4:CLOSE 4
```

Zero crossings were calculated by this program.

```
10 DIM ZC(5,1,13)
20 INPUT"ENTER INITIALS AND NUMBER OF PTS.";ID$,N
30 FOR MO=1 TO 6:ON MO GOTO 40,50,60,70,80,90
40 :MO$="GRA":GOTO 100
50 :MO$="SPL":GOTO 100
60 :MO$="FLX":GOTO 100
70 :MO$="EXT":GOTO 100
80 :MO$="PRO":GOTO 100
90 :MO$="SUP"
100 :FOR SN=1 TO 14
110 ::SN$=RIGHT$(STR$(SN),LEN(STR$(SN))-1)
120 ::N1$=ID$+MO$+".1."+SN$:N2$=ID$+MO$+".2."+SN$
130 ::ZX=0 :Q0=0
140 ::DOPEN#2,(N1$),D1:IF DS>1 THEN PRINT DS$;:IX=IX+1:PRINTIX:GOTO 230
145 ::INPUT#2,Y:IF Y>128 THEN Q0=1
150 ::FOR I=1 TO  N-1
160 :::INPUT#2,Y
170 :::IF Y<127 THEN Q1=0:GOTO 200
180 :::IF Y>128 THEN Q1=1:GOTO 200
190 :::Q1=Q0
200 :::IF Q1<>Q0 THEN ZX=ZX+1
210 :::Q0=Q1
220 ::NEXT I
230 ::DCLOSE
240 ::ZC(MO-1,0,SN-1)=ZX
250 ::ZX=0
260 ::DOPEN#2,(N2$),D1:IF DS>1 THEN PRINT DS$;:IX=IX+1:PRINTIX:GOTO 350
265 INPUT#2,Y:IF Y>128 THEN Q0=1
270 ::FOR I=1 TO N-1
280 :::INPUT#2,Y
290 :::IF Y<127 THEN Q1=0:GOTO 320
300 :::IF Y>128 THEN Q1=1:GOTO 320
310 :::Q1=Q0
320 :::IF Q1<>Q0 THEN ZX=ZX+1
330 :::Q0=Q1
340 ::NEXT I
350 ::DCLOSE :ZC(MO-1,1,SN-1)=ZX
370 :NEXT SN
380 NEXT MO
390 OPEN 4,4:CMD4
391 PRINT:PRINTSPC(30)"ZERO CROSSINGS":PRINT
392 PRINT:PRINTSPC(32)"ELECTRODE #1":PRINT
393 PRINT"SAMPLE  GRASP        SPLAY        FLEXION      EXTENSION    PRONATION"
394 PRINT"   SUPINATION"
395 PRINT"------  -----        -----        -------      ---------    ---------
396 PRINT"   ----------"
410 FOR I=0 TO 13
415 :PRINT"  "I+1;:LL=5-LEN(STR$(I+1))
420 :FOR J=0 TO 5
422 ::PRINTSPC(LL)ZC(J,0,I);:LL=11-LEN(STR$(ZC(J,0,I)))
424 :NEXT
426 :PRINT:NEXT
435 PRINT:PRINTSPC(32)"ELECTRODE #2":PRINT
440 PRINT"SAMPLE  GRASP        SPLAY        FLEXION      EXTENSION    PRONATION"
444 PRINT"   SUPINATION"
445 PRINT"------  -----        -----        -------      ---------    ---------
446 PRINT"   ----------"
450 FOR I=0 TO 13
455 :PRINT"  "I+1;:LL=5-LEN(STR$(I+1))
460 :FOR J=0 TO 5
462 ::PRINTSPC(LL)ZC(J,1,I);:LL=11-LEN(STR$(ZC(J,1,I)))
464 :NEXT
466 :PRINT :NEXT
480 PRINT#4:CLOSE ALL
```

AR coefficients were estimated using this program called "ARM".

```
10 DIM BETA(14,5),YD(300),TM(5,5)
20 N=300
30 INPUT"ENTER INITIALS";ID$:PRINT:INPUT"ENTER ORDER OF AR MODEL";P
40 OPEN4,4:CMD4
50 PRINTSPC(20)"AUTO REGRESSION COEFFICIENTS"
60 PRINT#4:CLOSE 4
70 FOR MO=1 TO 6:ON MO GOTO 80,90,100,110,120,130
80 :MO$="GRA":GOTO 140
90 :MO$="SPL":GOTO 140
100 :MO$="FLX":GOTO 140
110 :MO$="EXT":GOTO 140
120 :MO$="PRO":GOTO 140
130 :MO$="SUP"
140 :FOR EL=1 TO 2
150 ::EL$="."+RIGHT$(STR$(EL),LEN(STR$(EL))-1)+"."
160 ::FOR SN=1 TO 14
170 :::SN$=RIGHT$(STR$(SN),LEN(STR$(SN))-1)
180 :::NN$=ID$+MO$+EL$+SN$
190 :::DOPEN#2,(NN$),D1:IF DS>1 THEN PRINT DS$;:V=V+1:PRINTV:DCLOSE:GOTO 1070
200 :::FOR J=0 TO N-1
210 ::::INPUT#2,YD(J):IF DS>1 THEN PRINT DS$:V=V+1:PRINT V
220 :::NEXT J
230 :::DCLOSE
250 REM
260 REM CALCULATE AR COEF
270 REM FIRST FIND X'X, A (P+1)↑2 MATRIX
280 REM
290 :::TM(0,0)=N-P
300 :::FOR J=1 TO P
310 ::::FOR I=J TO P
320 :::::FOR K=P TO N-1
330 ::::::TM(J,I)=TM(J,I)+YD(K-I)*YD(K-J)
340 :::::NEXT K
350 :::::TM(I,J)=TM(J,I)
360 ::::NEXT I
370 ::::FOR K=P TO N-1
380 :::::TR(J)=TR(J)+YD(K)*YD(K-J)
390 :::::TM(0,J)=TM(0,J)+YD(K-J)
400 ::::NEXT K
410 ::::TM(J,0)=TM(0,J)
420 :::NEXT J
430 :::FOR K=P TO N-1
440 ::::TR(0)=TR(0)+YD(K)
450 :::NEXT K
470 REM
480 REM FIND (X'X)↑-1
490 REM
500 REM
510 :::FOR J=0 TO P
520 ::::YD(J)=J
530 :::NEXT J
540 :::FOR J=0 TO P
550 ::::CC=0
560 ::::M=J
570 ::::FOR I=J TO P
580 :::::IF (ABS(CC)-ABS(TM(J,I)))>0 THEN 610
590 :::::M=I
600 :::::CC=TM(J,I)
610 ::::NEXT I
620 ::::IF J=M THEN 670
630 ::::I=YD(M):YD(M)=YD(J):YD(J)=I
640 ::::FOR I=0 TO P
650 :::::S=TM(I,J):TM(I,J)=TM(I,M):TM(I,M)=S
660 ::::NEXT I
```

```
670 ::::TM(J,J)=1
680 :::FOR M=0 TO P
690 :::::TM(J,M)=TM(J,M)/CC
700 :::NEXT M
710 ::::FOR M=0 TO P
720 :::::IF J=M THEN 790
730 :::::CC=TM(M,J)
740 :::::IF CC=0 THEN 790
750 :::::TM(M,J)=0
760 :::::FOR I=0 TO P
770 ::::::TM(M,I)=TM(M,I)-CC*TM(J,I)
780 :::::NEXT I
790 ::::NEXT M
800 :::NEXT J
810 :::FOR J=0 TO P
820 ::::IF YD(J)=J THEN 920
830 ::::M=J
840 ::::M=M+1
850 ::::IF YD(M)=J THEN 870
860 ::::IF P>M THEN 840
870 ::::YD(M)=YD(J)
880 ::::FOR I=0 TO P
890 :::::CC=TM(J,I):TM(J,I)=TM(M,I):TM(M,I)=CC
900 ::::NEXT I
910 ::::YD(J)=J
920 :::NEXT J
940 REM
950 REM FIND (X'X)↑-1 X'Y WHICH IS BETA
970 REM
980 :::FOR J=0 TO P
990 ::::FOR I=0 TO P
1000 :::::BETA(SN-1,J)=BETA(SN-1,J)+TM(J,I)*TR(I)
1010 :::::TM(J,I)=0:REM CLEAR ARRAY
1020 ::::NEXT I
1030 ::::BETA(14,J)=BETA(14,J)+BETA(SN-1,J)
1040 :::NEXT J
1045 :::FOR J=0 TO P
1046 ::::TR(J)=0
1049 :::NEXT J
1050 REM
1060 REM
1070 ::NEXT SN
1080 ::OPEN4,4:CMD4
1090 ::PRINTSPC(12)MO$" ELECTRODE #"EL:PRINT
1100 ::PRINT"SN# ";
1110 ::FOR J=0 TO P
1120 :::BETA(14,J)=BETA(14,J)/14:REM FINISH CALCULATING THE BETA AVERAGES
1130 :::PRINT"B";J;SPC(11);
1150 ::NEXT J
1160 ::PRINT
1170 ::PRINT"—— ";
1180 ::FOR J=0 TO P
1190 :::PRINT"——"SPC(12);
1200 ::NEXT J
1210 ::PRINT
1220 ::FOR SN=0 TO 14
1230 :::PRINT SN+1;:LL=4-LEN(STR$(SN+1))
1240 :::FOR J=0 TO P
1250 ::::PRINTSPC(LL)BETA(SN,J);
1260 ::::LL=14-LEN(STR$(BETA(SN,J)))
1270 ::::BETA(SN,J)=0
1280 :::NEXT J
1290 :::PRINT
1300 ::NEXT SN
1310 PRINT#4:CLOSE 4
1320 :NEXT EL
1330 NEXT MO
```

APPENDIX C3

Medium contraction signals were identified with this algorithm. A worst case accuracy of 71.7% was achieved. It utilizes variance and zero crossing feature space and autoregressive modeling.

```
10 DIM B(11,4),Y1(199),Y2(199)
20 DATA 5.32148702,1.60921968,-.401345642,-.392139702,.145923066
30 DATA 3.64704741,1.79681069,-.613716866,-.428523092,.216939391
40 DATA 2.67398898,1.82686176,-.625129529,-.443988396,.221364564
50 DATA 11.8959459,.989642729,.187889349,-.1042597113,-.164565243
60 DATA 2.83598256,1.73861925,-.490649121,-.453790162,.18377113
70 DATA 7.29340983,1.34426129,-.0372945320,-.307912267,-.0552968730
80 DATA 2.57077127,1.87297085,-.720172125,-.365288417,.192265786
90 DATA 2.65959554,1.85725526,-.638524152,-.483946246,.244337499
100 DATA 10.32198299,1.107780027,.1566344573,-.1547962768,-.1921587075
110 DATA 2.19473556,1.77799732,-.486651833,-.516679739,.2081093042
120 DATA 3.79522857,1.66513608,-.377711981,-.495869325,.178146854
130 DATA 3.99656061,1.74395565,-.488238354,-.485633971,.198642304
140 FOR J=0 TO 11
150 :FOR I=0 TO 4
160 ::READ B(J,I)
170 :NEXT I
180 NEXT J
190 INPUT"ENTER N";N
200 FOR MO=1 TO 6:ON MO GOTO 210,220,230,240,250,260
210 MO$="GRA":GOTO 270
220 MO$="SPL":GOTO 270
230 MO$="FLX":GOTO 270
240 MO$="EXT":GOTO 270
250 MO$="PRO":GOTO 270
260 MO$="SUP"
270 FOR SN=1 TO  15
280 :SN$=RIGHT$(STR$(SN),LEN(STR$(SN))-1)
290 N1$="TEST"+MO$+".1."+SN$:N2$="TEST"+MO$+".2."+SN$
300 Q0=0:X1=0:X2=0:W1=0:W2=0:Z1=0:Z2=0:P0=0
310 DOPEN#2,(N1$),D1:IF DS>1 THEN PRINT DS$:DCLOSE:GOTO 790
320 INPUT#2,Y1(0)
330 DOPEN#3,(N2$),D1:INPUT#3,Y2(0)
340 X1=X1+Y1(0):X2=X2+Y1(0)*Y1(0):IF Y1(0)>128 THEN Q0=1
350 W1=W1+Y2(0):W2=W2+Y2(0)*Y2(0):IF Y2(0)>128 THEN P0=1
360 FOR K=1 TO N-1
370 INPUT#2,Y1(K):X1=X1+Y1(K):X2=X2+Y1(K)*Y1(K):IF Y1(K)<127 THEN Q1=0:GOTO 40
380 IF Y1(K)>128 THEN Q1=1:GOTO 400
390 Q1=Q0
400 IF Q1<>Q0 THEN Z1=Z1+1
410 Q0=Q1
420 INPUT#3,Y2(K):W1=W1+Y2(K):W2=W2+Y2(K)*Y2(K):IF Y2(K)<127 THEN P1=0:GOTO 45
430 IF Y2(K)>128 THEN P1=1:GOTO 450
440 P1=P0
450 IF P1<>P0 THEN Z2=Z2+1
460 P0=P1
470 NEXT K
480 DCLOSE
490 V1=(N*X2-X1*X1)/(N*(N-1)):V2=(N*W2-W1*W1)/(N*(N-1))
500 REM
510 REM
520 IF(V2<60) THEN MM=3:GOTO 740
530 IF(V1<12)AND(Z1<9)THEN MM=4:GOTO 740
540 IF(V1<9.45*Z1+10)AND(V1<-10*Z1+140) THEN MM=6:GOTO 740
550 REM
```

```
570 REM
580 M1=1E10:M2=1E10
590 FOR J=0 TO 5
600 I=J+6:E1=0:E2=0
610 FOR K=4 TO N-1
620 X=Y1(K)-B(J,0)-B(J,1)*Y1(K-1)-B(J,2)*Y1(K-2)-B(J,3)*Y1(K-3)-B(J,4)*Y1(K-4)
630 E1=E1+ABS(X)
640 X=Y2(K)-B(I,0)-B(I,1)*Y2(K-1)-B(I,2)*Y2(K-2)-B(I,3)*Y2(K-3)-B(I,4)*Y2(K-4)
650 E2=E2+ABS(X)
660 NEXT K
670 IF E1<M1 THEN M1=E1:C1=J+1
680 IF E2<M2 THEN M2=E2:C2=J+1
690 NEXT J
700 IF ((V2>411)AND(C1=5))OR(C1=3) THEN MM=2:GOTO 740
710 IF ((C1=5)AND(C2=5))OR(C1=1)OR(C1=2) THEN MM=5:GOTO 740
720 IF (V1<214)AND(V1>50*Z1-420) THEN MM=1:GOTO 740
730 MM=5
740 OPEN4,4:CMD4
750 PRINT"THE MOTION WAS "MO$" #"MO"  THE COMPUTERS GUESS IS...";MM
760 PRINTC1;C2;Z1;Z2;V1;V2;
770 IF MM=MO THEN CC=CC+1
780 PRINT#4:CLOSE 4
790 NEXT SN
800 NEXT MO
810 OPEN4,4:CMD4
820 PRINT"THE OVERALL ACCURACY IS";CC*10/6;"%"
830 PRINT#4:CLOSE 4
```