Upper Extremity Limb Function Discrimination Using EMG Signal Analysis

PETER C. DOERSCHUK, STUDENT MEMBER, IEEE, DONALD E. GUSTAFSON, MEMBER, IEEE, AND ALAN S. WILLSKY, SENIOR MEMBER, IEEE

Abstract—A signal analysis technique is developed for discriminating a set of lower arm and wrist functions using surface EMG signals. Data were obtained from four electrodes placed around the proximal forearm. The functions analyzed included wrist flexion/extension, wrist abduction/adduction, and forearm pronation/supination. Multivariate autoregression models were derived for each function; discrimination was performed using a multiple-model hypothesis detection technique. This approach extends the work of Graupe and Cline [1] by including spatial correlations and by using a more generalized detection philosophy, based on analysis of the time history of all limb function probabilities. These probabilities are the sufficient statistics for the problem if the EMG data are stationary Gauss-Markov processes. Experimental results on normal subjects are presented which demonstrate the advantages of using the spatial and time correlation of the signals. This technique should be useful in generating control signals for prosthetic devices.

I. Introduction

IN THIS paper we explore the design of a system using modern digital signal processing techniques to generate control signals for a multifunction lower arm prosthesis from a set of surface electromyogram (EMG) signals. The main body of work in this area has been aimed toward estimating the forces generated in a set of muscles and then using these estimates as the input to a kinematic model of the intact limb. The outputs of this model are limb function forces and/or velocities that can be used to control the servos of a particular prosthesis design. This is a two step process: 1) force estimation for a set of muscles followed by 2) limb function estimation. A selection of references for the following discussion would be Mann [2], Jacobsen and Mann [3], Mann and Reimers [4], Taylor and Finley [5], Kreifeldt [6], and Hogan [7].

Force estimation is usually done by measuring the total average power in an EMG signal and equating that to the force in the muscle directly below the electrode. This approach provides some information concerning muscle force, but it also has limitations.

1) The spectral shape or temporal signature of the EMG signal is not examined. If these characteristics change when conditioned on muscle force or muscle location relative to the electrode, then there is additional information for force estimation in the single muscle or a set of muscles that is not being used.

Manuscript received August 13, 1980; revised June 16, 1982. The work of P. C. Doerschuk was supported by a Fannie and John Hertz Foundation Fellowship.

P. C. Doerschuk and A. S. Willsky are with the Department of Electrical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139.

D. E. Gustafson is with Scientific Systems, Inc., Cambridge, MA 02140.

2) The EMG signal from an electrode above a muscle is not just a response to activity in that particular muscle. Rather, additional activity from other muscles is conducted through the tissue to be picked up by that electrode (i.e., crosstalk between different leads). Any method based on examining the energy in an EMG signal and associating it with the muscle directly below the corresponding electrode must regard these additional signal components as noise. However, it may be possible to extract additional information concerning the activities of muscles that are distant from the electrode by proper processing of the available EMG signals. In addition, it may be possible to design an algorithm in which an electrode failure can be tolerated with minimal performance loss by exploiting equivalent information in other channels.

3) Using the average power in a signal to estimate the force of the muscle directly below that electrode implies that a system requires a number of electrodes at least as great as the number of force estimates to be used. However, if techniques are applied to circumvent the limitations described in 1) and 2), it may be possible to derive N muscle forces estimates from fewer than N electrodes.

The transformation of muscle force estimates to estimates of limb function and then to servocontrol signals is generally done by taking fixed linear combinations of the processed EMG signals. In the sequel, this two step approach will be refered to as the power discrimination method (PDM).

In this paper, the approach we will take is to process the EMG signals as stochastic processes and to take direct account of the spectral shape and crosstalk between channels. Furthermore, instead of estimating muscle force and then using a model of an intact limb to derive limb function estimates, we will attempt to estimate limb function directly from the EMG. In Section II we discuss the evidence for auto- and cross correlations in the EMG signal which form the basis for our approach and review the work of other investigators of this problem, especially that of Graupe [1], [8]. In Section III we describe our approach in detail and in Section IV we present experimental results. Finally, Section V contains a discussion and conclusions.

II. Background

A. Evidence of Spectral and Cross Correlation Information

Several researchers have suggested that the predominant frequencies for different muscles lie in different frequency bands (cf. Sato [9], Scott [10], Kwatny *et al.* [11]). Spectral differences of this type are intrinsic to the muscles themselves and are not concerned with the properties of the conduction media and electrode placement. In addition, there is evidence

0018-9294/83/0100-0018$01.00

that these spectral properties are modified by the conduction media. Dhareshwar [12] found that the spectrum of the measured EMG was a function of the distance between the contracting fibers and the electrode. He found that the high-frequency components were attenuated more rapidly than were the low-frequency components. This implies that even if all muscles have identical frequency characteristics, it should be possible to differentiate between the signals at an electrode pair due to different muscles because of their different distances from the electrode pair. Thus, there are two sources of information in an EMG signal concerning which muscles are active—the differing spectral characteristics of each source and the differing transfer functions from each source to the electrode location. This result implies that discriminatory information is contained in the cross correlation between different electrode pairs.

Cross correlation is also thought of as a result of motor unit signal synchronization. The Piper rhythm is a conspicuous oscillation in the frequency range between 40–50 Hz and has been assumed to indicate coupling between motor units (Adrian [13], Fex and Krakau [14]). Person and Kudina [15] and Person and Libkind [16] used measurements of cross correlations measured by surface electrodes while studying this question and found values as high as 0.5–0.7.

Lindstrom and his co-workers have taken a theoretical approach in which they solve Laplace's equation subject to specified boundary conditions (see Lindstrom [17]). Power spectral calculations in Lindstrom [17], [18] and Lindstrom and Broman [19] indicate that low-frequency components of the motor unit potentials can be propagated over relatively long distances with little damping. This is in qualitative agreement with Dhareshwar's [12] work mentioned above.

B. Previous Approaches to EMG Signal Processing

Most present approaches to prosthesis control are concerned with estimating muscle force from the myoelectric signal. Then, Newton's laws and knowledge of the kinematics of the intact musculoskeletal system provide sufficient constraints to completely determine the system. Hogan [7] emphasizes this point strongly. Estimation of force requires nonlinear processing of the EMG since the myoelectric power spectrum does not contain zero frequency components. The usual approach is to assume that total force is proportional to the power in the electromyogram signal and this technique has been used in several systems (Mann [2], Jacobsen and Mann [3], Childress [20]). The estimation procedure for this approach involves two basic steps: 1) rectification and 2) smoothing. A zero-memory rectifier is used to demodulate the observed EMG signal. Some type of smoothing is then done on the demodulated signal to generate the force estimate.

Hogan [7] has taken a more sophisticated approach to muscle force estimation. He assumes that the observed scalar EMG signal $y(t)$ is a zero-mean Gaussian random process with variance parameter $\sigma(t)$. In turn, $\sigma(t)$ is related to the force $F(t)$ via $\sigma^2(t) = g(F(t))$, where $g(\cdot)$ is an invertible nonlinear function determined by experiment. Since the frequency content of $F(t)$ is much lower than for $y(t)$, the spectrum of the EMG signal $y(t)$ may be written in the form $S_y(\omega) = H_n^2(\omega) \cdot g(F(t))$, where $H_n(\omega)$ is a shaping filter specifying the high-frequency behavior of $y(t)$. This factorization is only an approximation since Kaiser and Petersen [21] and Sherif *et al.* [22] have presented evidence that the shape of the EMG spectrum does vary with force. However, Sherif *et al.* [22], modeling the medial deltoid muscle with a (1, 1, 1) autoregressive integrated moving average model (see Box and Jenkins [23]), show that the variation with load of the shape of the EMG spectrum during the "mobilization" and "buildup" phases of the contraction is negligible and that the variation during the "activation" phase is small—for instance, the autoregression coefficient moves from the 0.55–0.65 range to the 0.60–0.73 range when the load is increased from 0 to 1.2 kg (see Table I of Sherif *et al.* [22]). On the other hand, the residual variance increased by an order of magnitude under the same change in load. This indicates that Hogan's [7] assumption may be a very good approximation of reality. Hogan [7] then obtains the force estimate by maximum likelihood estimation of $g(\cdot)$ and inversion of $g(\cdot)$ to obtain the estimate of $F(t)$.

The muscle force estimates must be combined into actuator control signals in some manner. Generally, for multifunction prostheses, multiple EMG channels have been required (Taylor and Finley [5]) and pattern recognition ideas have often been employed to derive the actuator control signals (cf. Harrison [24], Lawrence *et al.* [25].) Other, more sophisticated, and physiologic approaches have also been used. For example, Jacobsen and Mann [3] have used the biomechanical kinematics of the upper arm and shoulder to derive constraints relating shoulder kinematic variables to upper arm kinematic variables. Then, using the EMG derived estimates of shoulder muscle forces, they are able to compute what values the upper arm kinematic variables must take.

C. The Work of Graupe [1], [22]

In his work on EMG prosthesis control, Graupe has taken advantage of spectral properties of the EMG signal and shown that these properties change when conditioned on different limb functions. From a single EMG lead, he has reported the ability to control five limb functions in real time with an 85 percent success rate. Discrimination of limb function was complete within 0.2 s of the initiation of that function. Graupe defined the spectra of each of his limb function classes by an autoregressive (AR) model. Thus, for each limb function m, $1 \leq m \leq M$, he assumed a scalar model of the form

$$y_m(k) = \sum_{j=1}^{p} a_{m,j} y_m(k-j) + e_m(k) \tag{1}$$

where $y_m(k)$ is the mth limb function signal at time k, $a_{m,j}$ is the jth regression coefficient for the mth limb function, $e_m(k)$ is the one-step-ahead prediction error for the mth limb function at time k, and p is the order of the autoregression model. This set of M models is derived in an off-line calculation made by a least squares procedure that minimizes the set of cost functions

$$J_m = \sum_{i=p+1}^{N} e_m^2(i)$$

where N was 200 and the sampling rate was 5 kHz. This gives a window of 0.04 s. Then, still off-line, he computes the second-order statistics for the one-step-ahead prediction errors

$$\bar{S}_m = \frac{1}{N-p-1} \sum_{i=p+1}^{N} (y_m(i) - \sum_{j=1}^{p} a_{m,j} y_m(i-j))^2; \quad m = 1, \cdots, M.$$

Finally, by experiment, Graupe chooses a set of M parameters $\rho_1, \cdots, \rho_M$ that will be discussed in the sequel. Graupe's determination of the autoregression model order p is apparently done by comparing the final results provided by different orders. He has generally used $p = 3$ or $p = 4$.

In the on-line operation mode, Graupe determines which limb function model gives the best fit to the current data. This is done by calculating the sample second-order statistics for the one-step-ahead prediction errors using the mth limb function model on data windows of specified length, say N_1. For data up to and including $y(i)$, he computes

$$S_m(i) = \sum_{k=i-N_1+1}^{i} (y(k) - \sum_{j=1}^{p} a_{m,j} y(k-j))^2; \quad i > N_1 + p.$$

In addition, the signal energy

$$E(i) = \sum_{k=i-N_2+1}^{i} y^2(k)$$

is calculated over a window of length N_2. The controller activates a limb function if $E(i) \geq E_{\min}$, where $E_{\min}$ is a set minimum energy. If a limb function is to be activated, that function m is chosen which satisfies $S_m < \rho_m \bar{S}_m$. These tests are designed to ensure first that there is a signal present and then to choose the limb function whose model best fits the current data using the cost function originally used to derive the model. Graupe does not address the possibility that two or more limb functions will simultaneously satisfy the selection criteria.

Graupe's work demonstrates very clearly that the spectrum of an EMG signal changes when conditioned on limb function. Furthermore, he shows that one can proceed directly from the EMG signal to limb function estimation without passing through explicit muscle force estimates. This is also a part of our approach. However, there are also several weaknesses in Graupe's approach, primarily concerning his on-line processing techniques.

1) Graupe's decision rules are not derived from his modeling assumptions. They do not extract all the information available from his models; as discussed above, there is no theoretical reason to believe that the criteria are self-consistent; and he is forced to introduce the free parameters $\rho_1, \cdots, \rho_m$, which have little physical/intuitive meaning.

2) Only a single lead was considered. While Graupe's results are remarkable considering he is only using one lead, they are clearly not sufficient for routine clinical use in which electrodes may fail or become too noisy for use. Hence, multiple EMG signals will be necessary and then, as discussed before, cross correlations will be important.

III. Method of Approach

On the basis of the prior discussion, three goals of EMG signal processing that have never been fully realized are 1) to account fully for spectral information, 2) to account fully for cross correlation information and 3) non-ad-hoc decision algorithms. In our opinion, the most straightforward way to achieve these goals is to treat the EMG signals as a vector-valued stochastic process and view the discrimination problem as a statistical decision problem. For the purpose of the present study, it is assumed that the models are linear and time invariant and may be modeled as vector autoregressive processes. Thus, we have the set of models

$$y(k) = \sum_{j=1}^{p} A_{m,j} y(k-j) + e_m(k); \quad m = 1, \cdots, M \tag{2}$$

where $y(k)$ is the observed $L \times 1$ vector EMG signal, $\{A_{m,1}, \cdots, A_{m,p}\}$ are $L \times L$ coefficient matrices, $e_m(k)$ is the one-step-ahead prediction error vector, subscript m refers to the limb function being modeled, M is the number of limb functions, and L is the number of electrodes. This model can be seen to be a generalization of the scalar AR model of Graupe. Note that lead crosstalk, instead of being treated as noise, enters as the off-diagonal terms in the $A_{i,j}$ matrices and the one-step-ahead prediction error covariance matrix S_i, i.e., crosstalk becomes part of the model.

The values of $A_{i,j}$ and S_i were determined for each limb function off-line by fitting them to actual EMG data recorded during execution of the particular limb function of interest. Least-squares parameter identification was performed using an efficient technique originally due to Levinson (cf. Kailath [26]). The parameters are computed from the serial autocorrelations. This technique allows different order models to be found in a particularly simple recursive manner.

On-line detection and identification of limb functions were done using the multiple model Kalman filter (cf. Lainiotis and Park [27] and Athans and Willner [28]). To describe this method, assume that data up to $y(k-1)$ are available and we wish to process the new data $y(k)$. Under the hypothesis that the ith function is taking place, the predicted value of $y(k)$ is

$$\hat{y}^i(k) = \sum_{j=1}^{p} A_{i,j} y(k-j).$$

We then compute the prediction error $e^i(k) = y(k) - \hat{y}^i(k)$. We now note that if limb function i is, in fact, taking place, then $e^i(k)$ is (ideally) a white noise process with covariance matrix S_i. This fact can be exploited in the following manner.

Suppose we wish to compute the probability $p_i(k)$ that limb function i is taking place, given data up to and including $y(k)$. Then, under the assumption that the data fit one of these models, we have from Bayes' rule

$$p_i(k) = \frac{P_i(y(k)|Y^{k-1})\, p_i(k-1)}{\sum_{i=1}^{M} P_i(y(k)|Y^{k-1})\, p_i(k-1)} \tag{3}$$

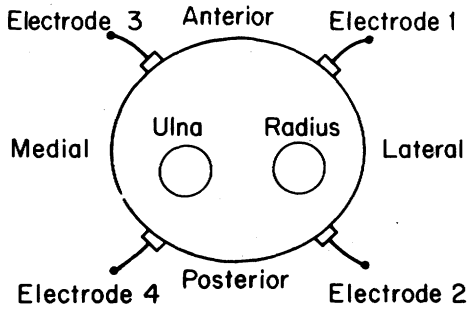


Fig. 1. A cross section, looking distally, of the right arm $\frac{1}{3}$ of the distance from elbow to wrist, showing the electrode locations.

where $Y^{k-1} = \{y(1), y(2), \cdots, y(k-1)\}$ and $P_i(y(k)/Y^{k-1})$ is the probability of occurrence of $y(k)$, given Y^{k-1} and limb function i. Assuming, for simplicity, that all of the data are Gaussian random variables, $P_i(y(k)|Y^{k-1})$ becomes Gaussian with mean $\hat{y}^i(k)$ and covariance matrix S_i. Equation (3) then provides an analytical recursion for solving for the desired probabilities. Once the probabilities for each limb function are known, simple decision logic can be used to detect the presence of a limb function.

IV. Experimental Results

A series of experiments was conducted to evaluate the approach of Section III (Doerschuk [29]). Four electrodes with self-contained preamplifiers were placed on the forearm $\frac{1}{3}$ of the distance from the elbow to the wrist. The electrodes were placed around the arm 90° apart, as shown in Fig. 1. Electrode specifications are shown in Fig. 2. This arrangement was chosen to record a complete, although coarse, sampling of EMG activity in the proximal forearm. No effort was made to place electrodes over particular muscles. An Ampex FR1300 analog tape recorder with 0-2.5 kHz bandwidth, signal-to-noise ratio of 44 dB rms, and total harmonic distortion of 1.2 percent was used. Five channels were recorded—one for each electrode and one for a control signal to indicate presence or absence of limb function. The raw EMG data were digitized (12 bits) at 2000 samples/s.

An example of the raw EMG data for the pronation limb function is presented in Fig. 3. The data were recorded with the elbow in the 90° flexed position while carrying a 1 kg weight. Thus, power in leads 1 and 3 is consistently high, reflecting activity of muscles required to counteract gravity. Lead 4 reflects the activity of pronator teres, a major forearm pronator, during the pronation motion, while lead 2 remains constant at a lower power level throughout the motion. A marked dc baseline can be seen in several of the leads, which we attributed to electrode potentials and to frequency mismatch in the demodulation of the analog data recording, which was played back at half speed. We did not wish to complicate our model by including a bias term, especially one whose magnitude, because these are not physiologic sources, would not be dependent upon the physiologic processes being modeled. Therefore, we removed the dc bias in a preprocessor stage by means of a high-pass filter. The filter has two key

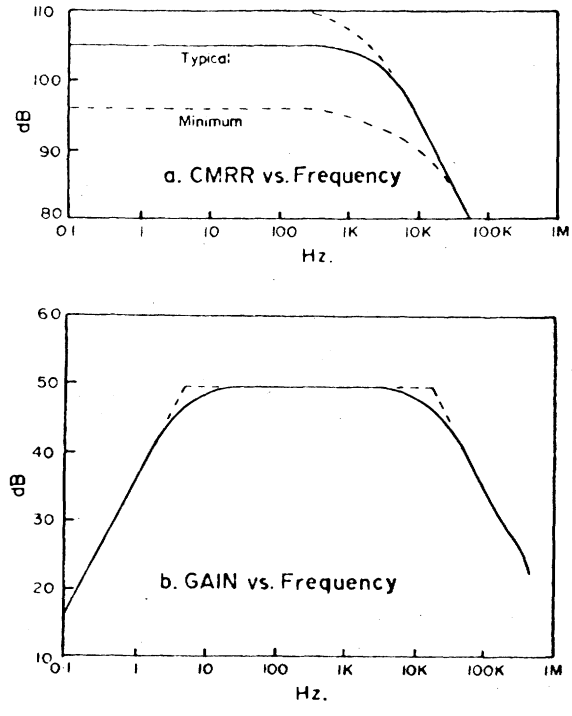


Fig. 2. CMRR and gain characteristics of the Motion Control, Inc., combined electrode amplifier units (data from MCI, Utah; modified from Hogan [2]).

specifications; it must have 1) essentially unit gain for $f > 20$ Hz since the EMG signal spectrum starts at approximately 20 Hz (Hogan [7], Kwatny [11]) and essentially zero gain near dc, and 2) linear phase since we are studying correlation between different signal leads and frequencies and do not want to introduce spurious phase shifts. The second requirement implies a finite duration impulse response filter whose impulse response $h(n)$ of duration N satisfies $h(n) = h(N-1-n)$, $0 \leqslant n \leqslant N-1$ (Oppenheim and Schafer [30]). This high-pass filter was realized by forming a low-pass filter estimate of the baseline and then subtracting this estimate from the EMG signal. For the low pass filter, we used a moving average filter with a 401 point window which has a half-power frequency of 2.21 Hz and a 100 ms delay when used at our digitization rate (2000 samples/s). The frequency response of this filter is shown in Fig. 4. The performance of the filter could be improved; for instance, the delay could be decreased by making a more sophisticated choice for the filter impulse response (see Oppenheim and Schafer [30] and the references therein), but this was not felt to be necessary for this study.

In our experiments, we did not vary the load carried by the subject. We propose to deal with different load levels by estimating the residual error covariance on-line for each limb function hypothesis and then using this estimate in the multiple model Kalman filter algorithm without altering the autoregression coefficients. This approach amounts to assuming that the shape of the EMG spectrum is independent of load and is motivated by Hogan's [7] factorization discussed in Section II-B. A second limitation of our experiments is that we have not considered day-to-day variation of the autore-

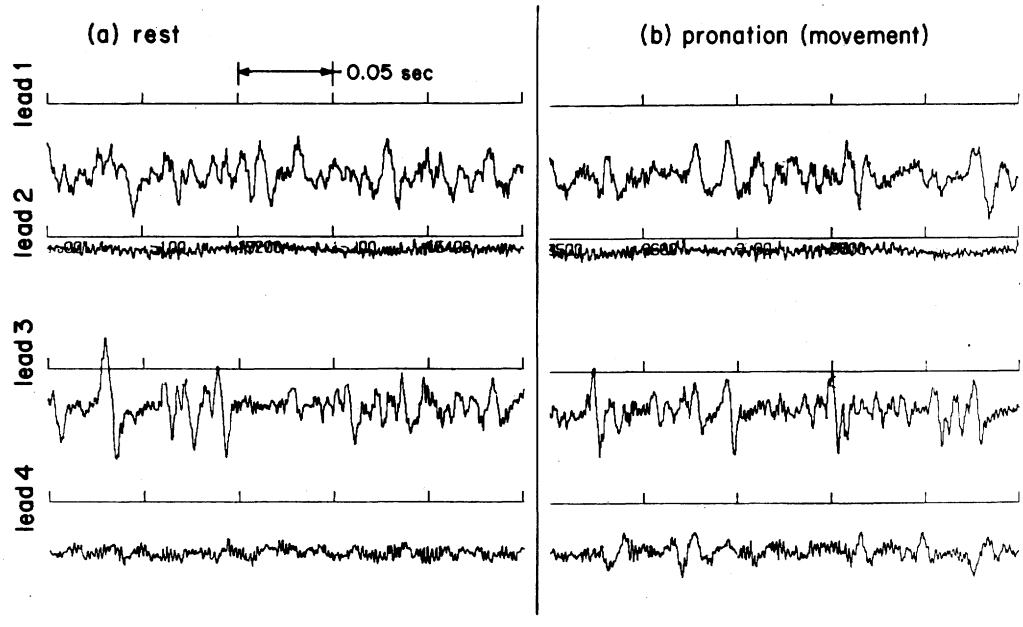


Fig. 3. Example of raw EMG data for pronation. Amplitude is in arbitrary digitizer counts.

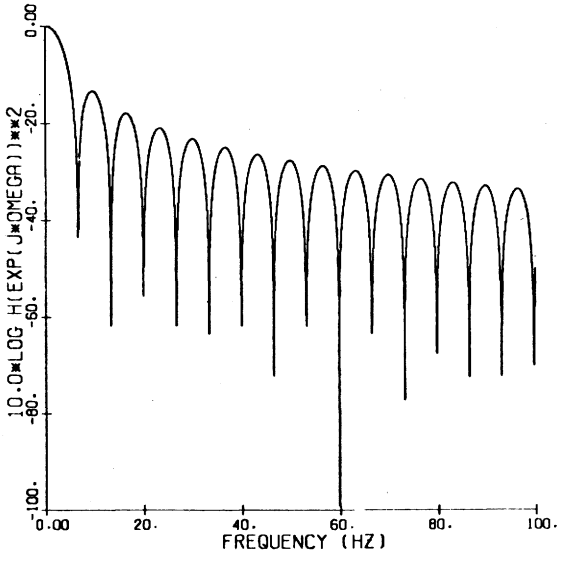


Fig. 4. Transfer function magnitude for a moving average filter averaging 401 points.

gression coefficients in a single subject, obviously an important point in a physical application. However, this issue has been considered previously by Sherif *et al.* [22] and their results, although for a different muscle, indicate that the autoregression coefficients are approximately constant.

A total of six different limb functions were modeled: 1) wrist flexion, 2) wrist extension, 3) wrist abduction, 4) wrist adduction, 5) forearm supination, and 6) forearm pronation. Each limb function was divided into four different phases. These were, in sequence, 1) rest, 2) initiation of function (movement), 3) hold, and 4) return to rest by reversing the movement. During phases 1) and 3), the limb is stationary, while during phases 2) and 4), it is in motion from one position to another. The duration of each phase was approximately 2 s so the complete limb function cycle took approximately 8 s.

The models for each limb function were obtained as follows. Serial autocorrelations were computed for each phase of each individual limb function, using data windows of 2000 samples (1 s) that were selected to lie in the middle of each of the phases. The values computed for different executions of the same limb function were not identical due to both the stochastic nature of EMG signals and the fact that limb movements are not absolutely repeatable. Thus, the serial autocorrelations from approximately five different executions of the same limb function were averaged before being used to determine the model parameters. In all experiments, the data used to determine model parameters (training set) were different from the data used to evaluate performance (test set).

A series of experiments was carried out to determine the effects of sampling rate and model order on discrimination capability. The results were similar for all limb functions and may be summarized as follows. The R^2 goodness-of-fit statistic did not increase for model orders greater than four. Akaike's information criterion (AIC) was used but had no minimum for model orders less than 20; hence, it was disregarded. Model orders of four and eight were tried at 2000 samples/s, with no significant improvement in discrimination noted for the eighth-order models. The sampling rate was halved and the same two experiments conducted. There was a significant performance degradation for both fourth- and eighth-order models and, as before, performance was not significantly improved using an eighth-order model. On the basis of these experiments, the following conclusions were reached.

1) Information useful in discriminating different limb func-

tions is contained in spectral frequency bands up to at least 1000 Hz.

2) A fourth-order autoregressive model for data sampled at 0.5 ms appears sufficient to capture most of the spectral discriminatory information.

In the sequel, we utilize a fourth-order model and 2000 samples/s sampling rate in all cases.

The probabilities generated by the multiple model hypothesis testing algorithm have much larger bandwidths than the actual limb movements which are band limited to less than 5 Hz (McRuer *et al.* [31], Neilson [32]). The larger bandwidth of the probabilities is due to the inaccuracies in our models of the EMG signal and low signal-to-noise ratio. Therefore, in order to aid the interpretation of the results, we have low-pass filtered the probabilities with a moving average filter having a 401 sample window, which has a half-power frequency of 2.21 Hz. All probabilities to be presented later in this paper have been processed using this filter.

Four different types of statistical structures were employed for each limb function. In order to describe these structures, it is helpful to think of the prediction error $e_m(k)$ in (2) as an excitation signal. From physical considerations, it follows that the unexcited system must be stable (Makhoul [33]). With this assumption, the structures may be divided into four types:

Type 1: Full AR structure.

Type 2: Spatially uncorrelated response structure. The matrices $A_{i,j}$ were constrained to be diagonal in the least squares optimization procedure. This corresponds to the assumption that the responses to the excitation at each electrode were independent. The matrices S_i were full.

Type 3: Spatially uncorrelated response and excitation structure. The matrices $A_{i,j}$ were as in Type 2 but, in addition, the matrices S_i were diagonalized by setting the off-diagonals to zero. This amounts to neglecting the cross correlation between the excitation processes of the different electrodes.

Type 4: Time uncorrelated structure (power discrimination method). The matrices $A_{i,j}$ were set to zero, so that the measured EMG was assumed to consist of only the excitation signal. That is, the model orders were set to zero. With this assumption, only signal power is used for discrimination. If, in addition, the off-diagonal components of S_i are set to zero (i.e., signals are spatially uncorrelated), the method reduces to that of Hogan [7] and Parker *et al.* [34].

Given a set of limb functions $F_1, \cdots, F_q$, we had originally hoped to be able to distinguish (i.e., have separate models for) phases 2), 3), and 4) for each limb function F_i, $1 \leqslant i \leqslant q$, plus a global rest model combining the rest segments [phase 1)] of all the limb functions F_i, $1 \leqslant i \leqslant q$. However, by combining models–i.e., by lumping together previously separate hypotheses–we were able to achieve much superior performance. Fig. 5(a) and (b) compare multiple model hypothesis testing (MMHT) filter probabilities using Type 1 models for an experiment in which all four phases were separately modeled [$M1$, $M2$, $M3$, and $M4$ in Fig. 5(a)], with the case where phases 2) and 3) [$M1$ in Fig. 5(b)] and phases 1) and 4) [$M2$ in Fig. 5(b)] have been combined. The improvement achieved by combining the phases is striking. Physically, we attribute the improvement achieved by combining phases 2) and 3) to the fact that the only difference between them is that the force applied in 2) is slightly larger such that it does not allow the static equilibrium that is achieved in 3) but rather results in a velocity. It seems that the algorithm is not able to capture the slight difference in force or velocity, which is quite understandable since

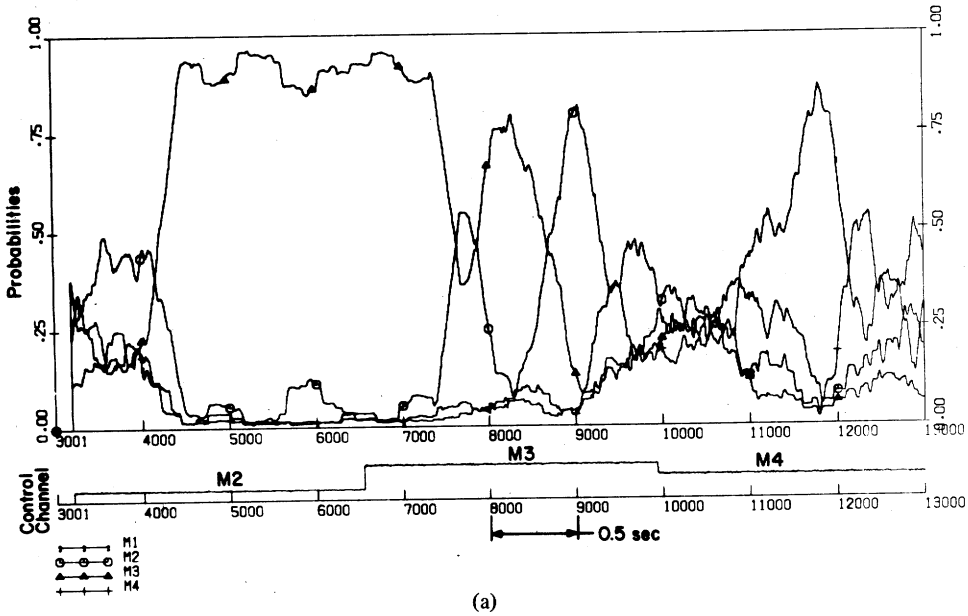
1) the information may not be present in the set of EMG signals we are studying, or
2) the information may be present, but the algorithm may not be able to capture it for several possible reasons: a) the information (exact force and/or velocity levels) is not contained in the models because the models are approximate and are averaged over ensembles which probably contain much wider variations in force and velocity, or b) the information is represented in the models but this information is obscured by the dominant similarities between the models.

Thus, the models representing phases 2) and 3) were effectively identical and hence, phases 2) and 3) could not be discriminated. By combining these hypotheses which have similar models, we leave only hypotheses whose models are different in some characteristic.

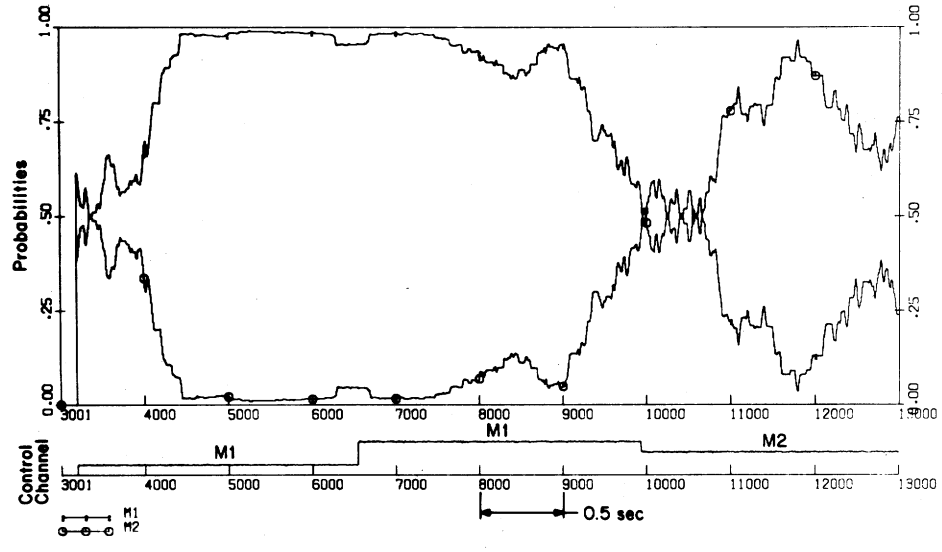
A similar explanation probably holds for the improvement seen on combining phases 1) and 4). In this case, the difficulty appears to be that phase 4) was primarily a passive relaxation where the arm is returned to the rest position by gravity and the potential energy stored in stretched tissues. Thus, the major difference between phases 4) and 1) is in the velocity. For the same reasons as before, the models for phases 4) and 1) were essentially identical and hence, phases 4) and 1) could not be discriminated.

In the sequel, we present results using composite models for each type of limb function in which the phases are combined as explained above. Henceforth, the class derived from combining phases 2) and 3) will be referred to as "motion X" or "forced motion X" in reference to active nature of the motion. The combination class derived from phases 1) and 4) will be referred to as "relaxation" without reference to a motion since this class is essentially the same for all motions. When a multiple model hypothesis testing filter is constructed for several motions, this class is always taken to include all the phases 1) and 4) data from all the motions included in the filter.

Fig. 6(a) and (b) show the effect of including spatial correlation (i.e., correlation between leads). The probabilities for five limb functions (wrist flexion/extension, forearm pronation/supination, and wrist abduction) and relaxation phase are plotted versus time. The true function is wrist flexion. In Fig. 6(a), a Type 1 structure is used, while in Fig. 6(b), a Type 2 structure is used (electrode correlations are not



(a)



(b)

Fig. 5. Pronation probabilities versus time. True function is pronation. Labels on the control channel indicate which model should have the largest probability at that time. Type 1 models. (a) Separate models ($M1$, $M2$, $M3$, $M4$) used for each of the four phases (1, 2, 3, 4). $M1$ = global model for rest, $M2$ = model for movement from rest to fully pronated position, $M3$ = model for holding the fully pronated position, $M4$ = model for movement from the fully pronated position back to rest. (b) Phases 1) and 4) (rest and movement from fully pronated position back to rest) have been combined into model $M1$ and Phases 2) and 3) (movement from rest to fully pronated position and holding the fully pronated position) have been combined into model $M2$.

included in the autoregressive models). The performance difference is seen to be relatively small during forced motion and relatively large during the relaxation phase. There is some confusion (overlap) with pronation during function initiation. This is probably due to the proximity of the pronator teres muscle (a forearm pronator) and the flexor carpi radialis and flexor carpi ulnaris muscles (wrist flexors) in the proximal forearm.

Fig. 7(a) and (b) demonstrate the effect of including time correlation. The data clearly show that use of time correlation [Fig. 7(a)]—i.e., a Type 1 structure—gives faster response during the initiation phase and does not degrade near the end of the motion. With no time correlation included [Fig. 7(b)]—i.e., a Type 4 structure—a strong decision of "supination" is indicated during the relaxation phase; with time correlation, the relaxation probability is weakly indicated.

Fig. 8(a) and (b) demonstrate the effect of using a variable number of leads. In Fig. 8(a), only lead 1 was used for discrimination of wrist abduction, while in Fig. 8(b), all four leads were used. With one lead, wrist abduction is strongly indicated correctly only about 50 percent of the time. Note that supination is transiently indicated at the transition between the initiation and hold phases of forced motion. With four leads, the performance is more robust; abduction is

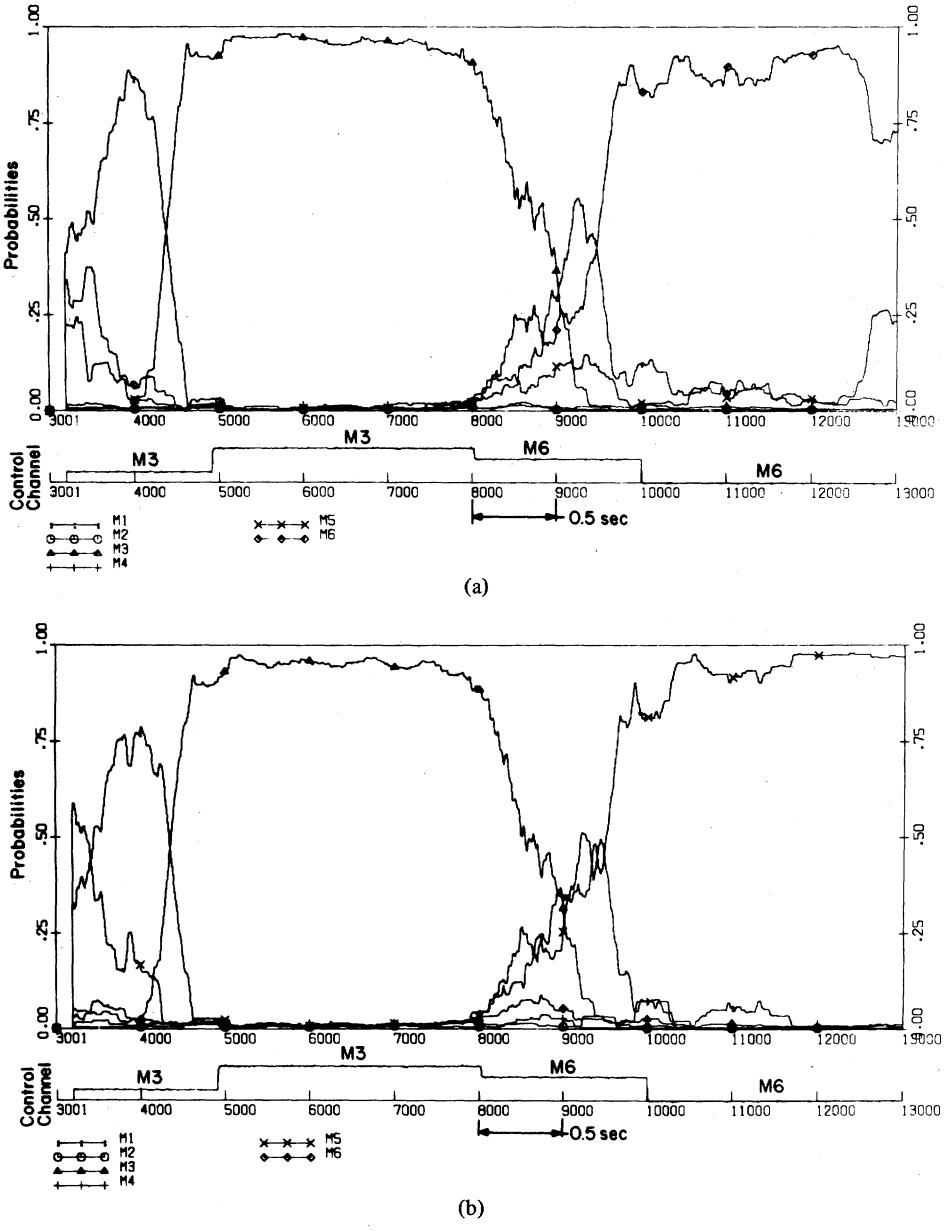


Fig. 6. Limb function probabilities versus time. Five force functions and rest are modeled. $M1$ = pronation, $M2$ = wrist abduction, $M3$ = wrist flexion, $M4$ = wrist extension, $M5$ = supination, $M6$ = global relaxation. True function is wrist flexion ($M3$). Labels on the control channel indicate which model should have the largest probability at that time. (a) Type 1 structure. (b) Type 2 structure.

strongly indicated over essentially the entire forced motion cycle. This robustness is due to the fact that four sources of information are being used rather than one. The same qualitative performance can be noted during the relaxation phase.

V. Discussion

In this paper, a conceptual approach to limb function discrimination is proposed based on modeling the EMG signals as stochastic processes to which probabilistic signal processing techniques are applied. The essential features of this approach are

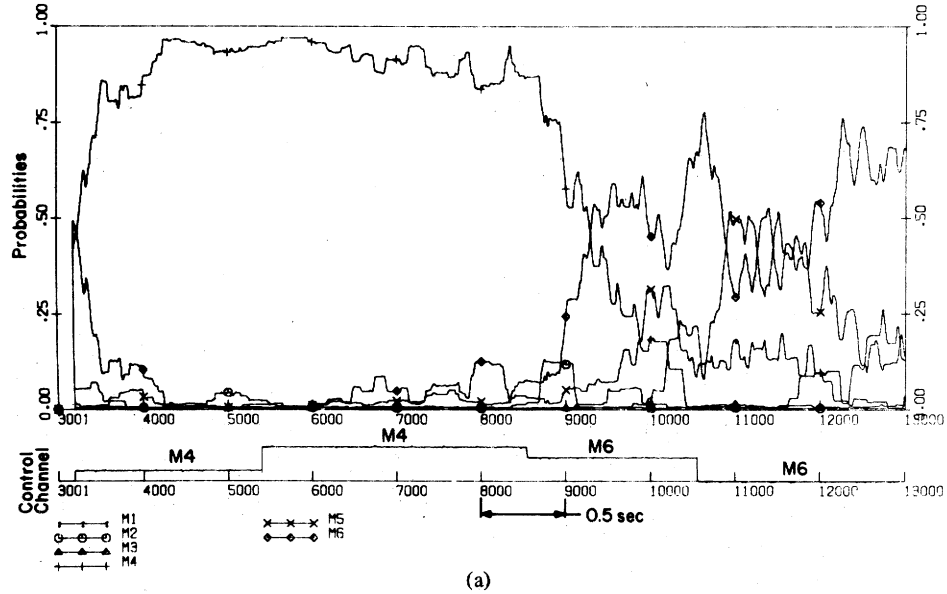
1) exploitation of the autocorrelations of the EMG signal measured at an electrode,

2) exploitation of the cross correlations between the EMG signals measured at separated electrodes, and

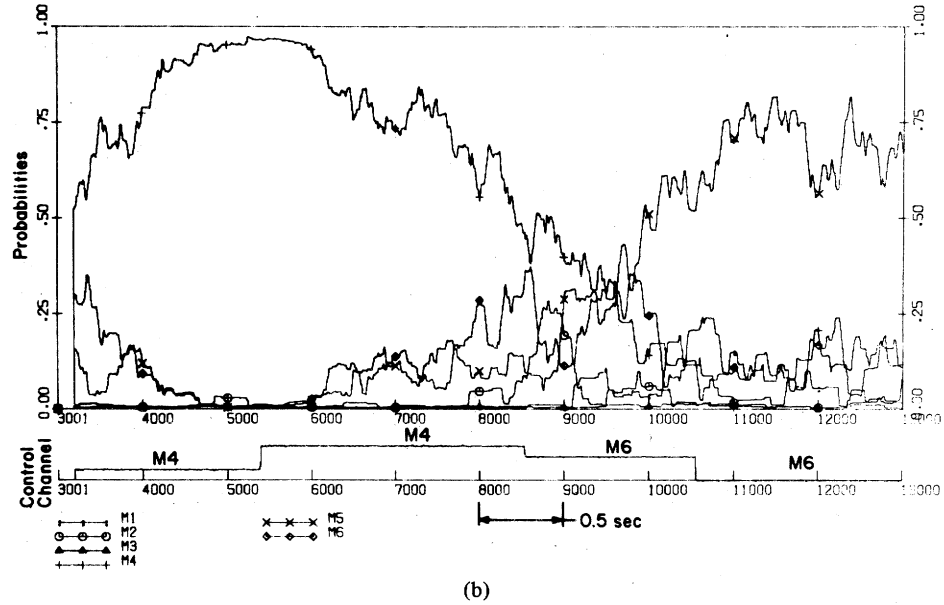
3) an optimal probabilistic combination of information from separate EMG leads into a set of sufficient statistics for prosthesis control. These statistics are the probabilities that the observed signal is generated by each of the limb functions and can be calculated recursively at each sample point.

We believe that the use of 2) and 3) in the context of EMG processing is new.

Models of the EMG signal in the form of vector autoregressive processes have been developed. Tests based on these models indicate that this approach has promise, although it is far from completely developed and additional testing is required. The most significant results may be summarized as follows.



(a)



(b)

Fig. 7. Limb function probabilities versus time. Five force functions and rest are modeled. $M1$ = pronation, $M2$ = wrist abduction, $M3$ = wrist flexion, $M4$ = wrist extension, $M5$ = supination, $M6$ = global relaxation. True function is wrist extension ($M4$). Labels on the control channel indicate which model should have the largest probability at that time. (a) Type 1 structure. (b) Type 4 structure.

1) Information useful in discriminating different limb functions is contained in spectral frequency bands up to at least 1000 Hz.

2) A fourth-order autoregressive model appears sufficient to capture most of the discriminatory information when used with a 0.5 ms sampling interval.

3) Discriminatory information is present in both the spatial and time correlation structure of the EMG signal.

4) It is important to select a set of limb functions, or combinations of limb functions, which yield mathematical models which are highly separable for a given electrode configuration.

As discussed above, this paper presents a conceptual approach to EMG signal processing and not a fully developed system. Among the areas requiring further work are

1) the possibility of proportional control—we have only considered on/off control in this paper,

2) the response time from initial A/D conversion to limb function detection,

3) detector performance when mixed limb functions are actuated, and

4) system robustness—how much retuning is necessary to achieve satisfactory performance for different operators and for the same operators at different times.

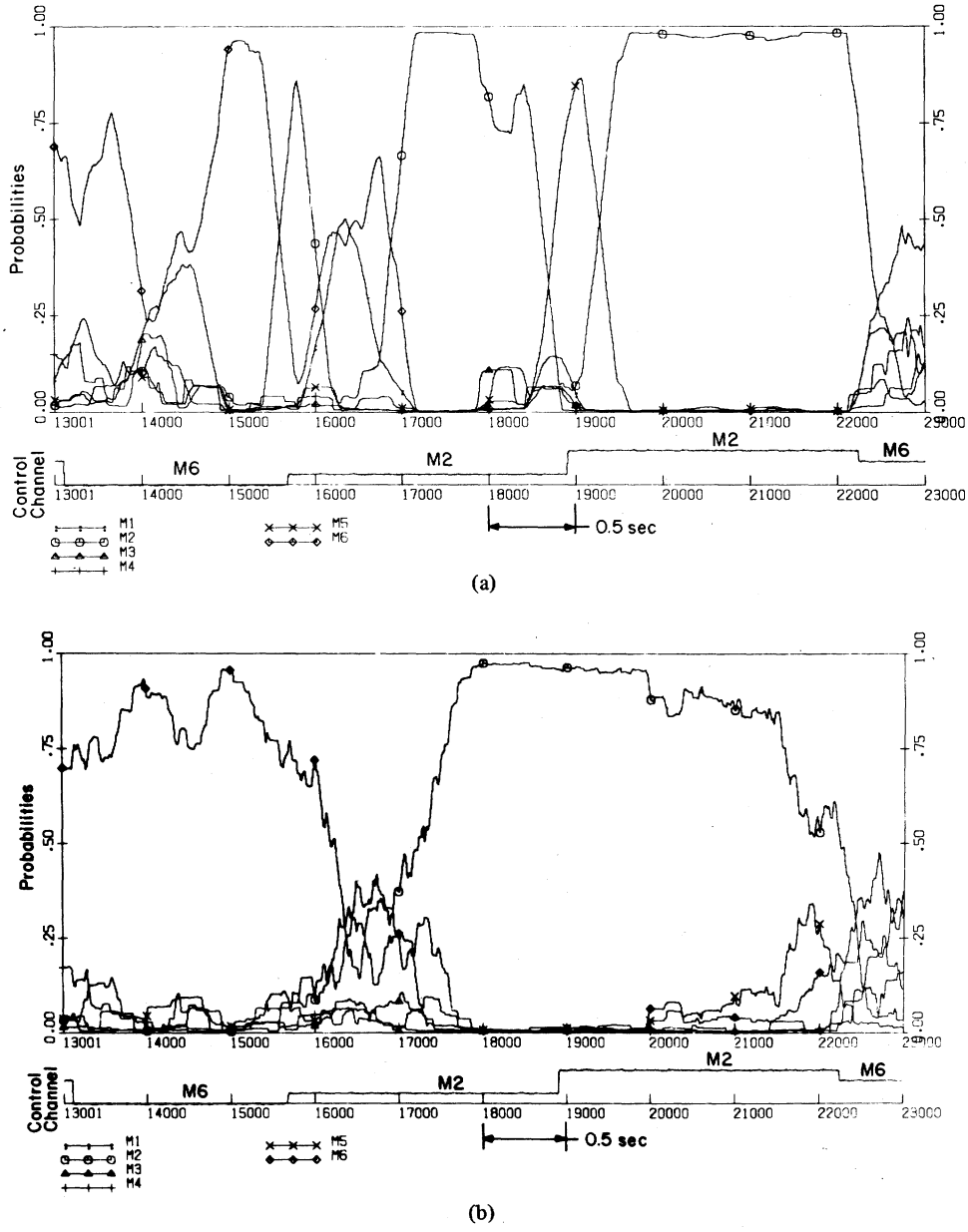


Fig. 8. Limb function probabilities versus time. Five force functions and rest are modeled. $M1$ = pronation, $M2$ = wrist abduction, $M3$ = wrist flexion, $M4$ = wrist extension, $M5$ = supination, $M6$ = global relaxation. True function is wrist abduction ($M2$). Labels on the control channel indicate which model should have the largest probability at that time. Type 1 structure. (a) Lead 1 only. (b) All four leads.

ACKNOWLEDGMENT

The authors would like to acknowledge the support of D. Grimes and P. Schluter, Massachusetts Institute of Technology, Cambridge, in the data acquisition phase of this project, and helpful discussions with Prof. S. C. Jacobsen of the University of Utah, Salt Lake City.

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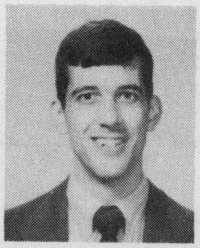
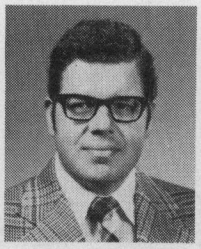


Peter C. Doerschuk (S'79) received the B.S., M.S., and E.E. degrees in electrical engineering from the Massachusetts Institute of Technology, Cambridge, in 1977, 1979, and 1979, respectively.

He is currently a Ph.D. candidate in electrical engineering at M.I.T. and an M.D. candidate in the Harvard University–M.I.T. Division of Health Sciences and Technology, Cambridge, MA. From 1977 through 1981 he held a Fannie and John Hertz Foundation Fellowship, and since 1981 he has been supported by a fellowship from the M.D.–Ph.D. Program of Harvard Medical School. He has held summer positions at the Charles Stark Draper Laboratory, Cambridge, MA (1976) and Scientific Systems, Inc. Cambridge, MA (1977 and 1978).

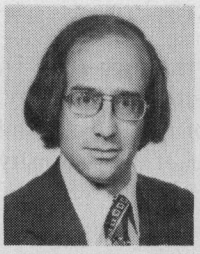
Mr. Doerschuk is a member of Sigma Xi, Tau Beta Pi, and Eta Kappa Nu.



Donald E. Gustafson (S'60–M'67) was born in Akron, OH, on June 6, 1938. He received the B.S.E.E. degree from Akron University, Akron, OH, in 1962, the M.S.E.E. degree from Santa Clara University, Santa Clara, CA, in 1966, and the Ph.D. degree in engineering from the Massachusetts Institute of Technology, Cambridge, in 1972.

From 1962 to 1966 he was with Lockheed Missiles and Space Company, Sunnyvale, CA, working on guidance and control systems for space vehicles and ballistic missiles. From 1966 to 1977 he was with the Charles Stark Draper Laboratory, Cambridge, MA, working principally on space vehicle guidance and navigation and biomedical signal processing. Presently, he is Vice President of Scientific Systems, Inc., Cambridge, MA, where he directs projects in biomedical signal processing, statistical estimation, financial analysis, and pattern recognition.

Dr. Gustafson is a member of Sigma Tau and Sigma Xi.



Alan S. Willsky (S'70–M'73–SM'82) was born in Newark, NJ, on March 16, 1948. He received the S.B. degree in aeronautics and astronautics and the Ph.D. degree in instrumentation and control, both from the Massachusetts Institute of Techology, Cambridge, in 1969 and 1973, respectively.

From 1969 through 1973 he held a Fannie and John Hertz Foundation Fellowship. He joined the faculty of the M.I.T. Department of Electrical Engineering and Computer Science in 1973, and is presently an Associate Professor of Electrical Engineering. Since 1974 he has been Assistant Director of the M.I.T. Laboratory for Information and Decision Systems. From February through June of 1977 he was Science Research Council Senior Visiting Fellow at Imperial College, London, England, and from September 1980 through January 1981 he was a Professeur Associé at the Université de Paris-Sud, Orsay, France. He is the author of one book, *Digital Signal Processing and Control and Estimation Theory: Points of Tangency, Areas of Intersection, and Parallel Directions* (M.I.T. Press, 1979). The paper "Relationships Between Digital Signal Processing and Control and Estimation Theory"

(*Proc. IEEE*, vol. 66, Sept. 1978), for which he was awarded the 1979 Alfred Noble Prize by the American Society of Civil Engineers and the 1980 Browder J. Thompson Memorial Prize Award by the IEEE, provides an introduction to many of the topics addressed in the book. He has recently coauthored an undergraduate text, *Signals and Systems*, with Prof. A. V. Oppenheim and Dr. I. T. Young (Englewood Cliffs, NJ: Prentice-Hall, 1982). He has written numerous papers on algebraic system theory, nonlinear filtering, failure detection, stochastic processes, and biomedical signal processing. His present research interests are in problems involving abrupt changes in signals and systems and the related problems of detection and reliability, the modeling and processing of spatially distributed random data, digital signal processing issues in control system design, and the analysis of stochastic processes and systems.

Dr. Willsky is a founder and member of the Board of Directors of Alphatech, Inc. In 1975 he received an award from the M.I.T. Graduate Student Council for outstanding teaching, and in August 1975, he received the Donald P. Eckman Award from the American Automatic Control Council. He is Editor of the M.I.T. Press series of books on signal processing, optimization, and control, was the Program Chairman for the 17th IEEE Conference on Decision and Control held in San Diego, CA, in January 1979, is an Associate Editor of the journals *Stochastics* and *Control and Systems Letters*, is a member of the Administrative Committee of the IEEE Control Systems Society, and was the Control Systems Society Program Chairman for the 1981 Bilateral Seminar on Control Systems sponsored by the IEEE Control Systems Society and the Chinese Association for Automation. He gave the opening plenary lecture at the 20th IEEE Conference on Decision and Control. He is a member of SIAM, AAAS, Sigma Xi, Sigma Gamma Tau, and Tau Beta Pi.

Accuracy of Dipole Localization with a Spherical Homogeneous Model

ROGER P. GAUMOND, MEMBER, IEEE, JIA-HOUNG LIN, STUDENT MEMBER, IEEE, AND DAVID B. GESELOWITZ, FELLOW, IEEE

Abstract—**Dipole localization methods (DLM's) with a spherical, homogeneous, isotropic model were applied to the problem of locating and characterizing simulated dipole sources of the brainstem acoustic evoked response (BAER) in cats. Dipole source parameters considered were chosen to be consistent with measurements of gross potential within the brainstem during the BAER. The steepest ascent method was used to solve the least-squares minimization problem on a set of noise-perturbed surface voltages to obtain parameters of a single assumed dipole source. The magnitudes of errors in dipole postion and in dipole moment vectors were calculated for two surface voltage location sets, two assumed dipole source locations, and a range of surface signal-to-noise ratios. An approximate analytic approach to the simulation results attributed DLM errors to an apparent "noise dipole" calculated as the dipole term in the multipole expansion of the added surface noise. The standard deviation of the "noise dipole" magnitude was directly proportional to the standard deviation of surface noise voltage and inversely proportional to the root of the number of surface voltages. This analytic result was in general agreement with the mean of the dipole moment parameter errors in the simulation study. It was found that recalculation of the surface voltage set from the solution dipole of the simulation problem or from the "noise dipole" of the analytic treatment resulted in an improvement of signal-to-noise ratio at the surface.**

INTRODUCTION

DIPOLE localization methods (DLM's) were originally developed for the study of the electrocardiogram [1] and were later applied to the electroencephalogram [2] and to evoked potentials [3], [4]. This study seeks to determine conditions under which the accuracy of DLM would be sufficient to identify the neural source of the brainstem acoustic evoked response (BAER) in cats at those instants when a single dipole source model is appropriate.

The BAER is a microvolt-level electrical signal measured on the scalp by response averaging during the first 10 ms following application of a brief acoustic stimulus. Recordings of the BAER from within cat brainstem [5] and on cats with brainstem lesions [6] have linked the succession of peaks in the surface response with the discharge response of successive relay nuclei in the ascending auditory brainstem pathway. This identification of BAER peak latency with individual brainstem nucleus has led to a host of clinical applications in neurological [7] and audiological [8] assessment. However, recent studies on animals [9] have indicated that several distinct neurological sites are simultaneously active during several instants of the BAER. This can complicate interpretation of BAER clinical data. We suggest that DLM techniques may shed additional light on BAER response origin in cat, the accepted animal model, and may eventually provide a basis for interpretation of BAER responses in humans when these responses are abnormal and the relationship of peak latency to specific neurological site is therefore unknown.

The cat brainstem recordings of Achor [10] indicate that at certain instants during the BAER, neuroelectric response is largely confined to one of several distinct areas. Since each such area lies well below the scalp, a single dipole source description may be particularly appropriate at such times. Also, single deep sources produce small voltage gradients on the surface, making DLM methods relatively insensitive to errors in

Manuscript received April 6, 1982; revised July 1, 1982. This work was supported by the National Science Foundation under Grant ECS-8106006, and by a grant from the Whitaker Foundation.

The authors are with the Department of Bioengineering, Pennsylvania State University, University Park, PA 16802.

0018-9294/83/0100-0029$01.00