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Parametric Analysis of Dynamic Postural Responses

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Abstract. A detailed theoretical understanding of postural control mechanisms must be preceded by careful quantification of both the deterministic and stochastic aspects of postural behavior of normal and abnormal subjects under various dynamic conditions. Toward this end, concise parametric transfer function plus noise models were derived for both shoulder and waist position data obtained by applying a linear anterior-posterior bandlimited pseudorandom disturbance to the base of support of human subjects. Model orders as well as model parameters were determined empirically. One advantage of this modeling procedure is the conciseness of the postural models, permitting easy statistical analysis of the data obtained under different dynamic conditions from many subjects. Model features, including pole and zero locations, from 6 normal subjects each tested on 5 consecutive days under 3 input amplitudes and eyes open and closed conditions are presented. The resulting transfer function models consist of only 1 or 2 poles near the integration position on the Z plane unit circle and 0 to 2 zeros. Locations of the poles indicate that the eyes closed responses are more oscillatory, less damped, and with higher gains than the eyes open responses. These transfer functions are similar to nonparametric ones of other authors. The noise model orders are also small. Their spectra are those of low pass systems. Also, the quantity and frequency range of the postural noise is positively related to the amplitude of platform motion as well as related to the presence or absence of vision.

1 Introduction

Upright human postural regulation is a complex motor function, dependent upon the integration of information from several sensory modalities and upon the properties of subsystems at the spinal and higher levels of central nervous control. Because postural sway can be measured easily, quickly, and noninvasively on human subjects, the posture control system is an excellent substrate for the study of human motor control mechanisms. Systems analysis has been useful in achieving understanding of many of the physiological processes which participate in the postural control system. For example, a great deal of effort has been invested in the development of theoretical models of the stretch reflex (Crago et al., 1976; Nichols and Houk, 1976; Poppele, 1973). Systems analysis has been useful in defining transduction properties of the semicircular canals (Goldberg and Fernandez, 1971), the otoliths (Fernandez and Goldberg, 1976), eye movements (Stark, 1968), and joint receptors (McCall et al., 1974).

If the posture control system with all its components were linear, it should be theoretically possible to piece together transfer functions for the subsystems to obtain a complete model and hence understanding of the posture control system as a conceptually simple servomechanism. Nashner (1972) took this approach when he developed a vestibular feedback model for human postural control. Others (Koozekanani et al., 1980; Stokic and Vukobratovic, 1979) have attempted to construct postural control models by making use of equations of motion for a single, double-stacked, or more elaborate inverted pendulum and various feedback laws.

Both theoretical and empirical considerations indicate that construction of a meaningful theoretical model of the posture control system is no small feat. Certainly the posture control system can be thought of as a complex system. Simon (1962) defines a complex system as follows: "Roughly, by a complex system I mean one made up of large number of parts that interact in a nonsimple way. In such systems, the whole

Present address: Kresge Hearing Research Institute, University of Michigan Medical School, 1301 E. Ann St., Ann Arbor, MI 48109, USA is more than the sum of parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole." Evidence for elaborate control structures in postural regulation abounds. Bernstein (1967) and Greene (1972) postulated that a hierarchial organization for motor control systems was necessary. The elementary subsystems such as those mentioned above are at the base of this hierarchical organization while the system output depends upon the performance of these lower systems and on higher level systems, which in turn depend upon performance of the lower levels. Nashner (1976) demonstrated evidence for synergies and hierarchical control in human posture. Synergies are marked coordinations of muscular activity of different parts of the body. Local control mechanisms, in which subsystems interact with each other and the environment in some optimal way that minimizes the need for higher level control have been demonstrated. An example of the latter is the evidence for a mass-spring model of motor control in unidirectional positioning tasks (Kelso and Holt, 1980; Polit and Bizzi, 1979). Recent investigations of postural control mechanisms of humans (Nashner, 1976; Nashner and Berthoz, 1978; Soechting and Berthoz, 1979) and of dogs (Schuster and Talbott, 1980; Talbott and Brookhart, 1980) have demonstrated that postural control strategies are context dependent and adaptive. Also, conscious control has been demonstrated to alter postural sway behaviour via changes in postural set (Seidel and Brauer, 1978, 1979), and in a biofeedback fashion utilizing auditory or visual feedback (Gantchev et al., 1979; Takeya, 1976).

An important preliminary step in the analysis of postural control mechanisms is careful quantification for large numbers of subjects under different conditions of the answer to the question: "What does the postural control system do?" Systems analysis provides answers in the time and frequency domains by maximizing information available from observation of the system's behavior. Such models can be evaluated from mathematical points of view such as control system theory in order to gain insights concerning the underlying biological systems. These insights can aid in the design of physiological experiments to explore the actual structure of the underlying system.

Control theoretical analysis of static postural behavior has been used as a tool in the analysis of postural mechanisms (Nashner, 1972; Dichgans et al., 1976; Diener et al., 1982; Aggashyan, 1972). Dynamic studies provide a more direct approach to the analysis of postural mechanisms and organization. One can achieve a description of the output of the postural control system (movement of some part of the body or EMG response, for example) with respect to some known induced disturbance such as tilting or translation of the base of support, motion of the visual surround (Diener et al., 1982; Dichgans et al., 1976), and vestibular stimulation (Kapteyn, 1972; Njiokiktjien and de Rijke, 1972). Dynamic studies are also more suitable for the study of systems possessing internal noise. Static postural sway can be considered the manifestation of the posture control system's internal noise, which, from a practical point of view, is the system's response to unknown inputs. Noise has been demonstrated to be a vital part of other physiological dynamic systems such as the pupillary control system (Stark, 1968) and muscles (Joyce and Rack, 1974; Marsden, 1978; Matthews and Muir, 1980). Thus, a description of postural dynamics is incomplete without a description of the concomitant noise. Dynamic studies of responses to disturbances of the base of support in several contexts have been done, including predictable sinusoidal inputs (Andres, 1979; Gantchev and Popov, 1973; Meyer and Blum, 1978; Diener et al., 1982), unpredictable inputs (Ishida and Imai, 1980; Meyer and Blum, 1978; Nashner, 1976), and absence of vision (Andres, 1979; Ishida and Imai, 1980; Diener et al., 1982). However, with the spectral methodology used to derive the transfer functions in these studies, the internal noise signal was ignored so that descriptions of the dynamics provided by the functional systems analysis were incomplete.

In this report is described a parametric black box model of the human postural control system in the contextural framework of a bandlimited pseudorandom disturbance applied to the base of support in a linear, anterior-posterior direction. The parameters of a noise model are estimated simultaneously with those of a transfer function, so that models for the postural noise under dynamic conditions for the first time are obtained. The models are simple linear time invariant difference equations which express the output (waist or shoulder position) as a weighted parametric sum of past outputs and past and present inputs, both deterministic (platform position) and stochastic (white noise). The sizes of the models are determined empirically as well as the values of the parameters. Models are estimated for the shoulder and waist motion responses to 360 dynamic trials for each of 6 normal subjects.

It is seen that satisfactory models can be obtained which possess small orders, so that statistical analysis of fundamental and derived model features can be easily done, permitting rigorous comparisons of responses under different dynamic conditions. Here, the comparisons are done for three different stimulus amplitudes and for eyes open and closed conditions. The pole and zero locations of both the noise model and the transfer function are the fundamental features since with the exceptions of gain terms, they provide complete descriptions of the models. Other features, such as selected transfer function gains, phase lags, and variance can be derived, so that comparison of these parametric transfer functions can be made with those derived nonparametrically by other authors. The variance of the noise portion can also be easily obtained.

2 Methods

2.1 Posture Measurement System

The posture measurement system consists of a stimulus delivery component, a response measurement component, and an LSI-11 microcomputer with 32 K of memory and necessary interfaces for data acquisition and analysis. Mass storage for data is provided by floppy discs. The characteristics of the posture measurement system have been described in detail elsewhere (Andres and Anderson, 1980), so that only a brief description is provided here.

The stimulus delivery system is a moving platform which translates the support base 0.457 m peak-to-peak in the plane of the floor. The support base is 0.61 m on a side, mounted on two parallel stainless steel rails with ball bushings. The drive mechanism is a 0.64 m per revolution lead screw with a preloaded ball bearing nut, driven by a *dc* torque motor which is controlled by a servo amplifier receiving velocity commands from the LSI-11 microcomputer through a $D-A$ converter. Measurements of the platform position are resolvable to the nearest 0.03 cm. Andres (1979) demonstrated that the frequency response of the platform was flat to over 3 Hz even when loaded with 77.3 kg subject and that minimal cues from factors as vibration or noise from the platform reached the subject.

The response measurement component is composed of two digital line scan cameras which sense the average position of the sagittal plane body silhouette of the subject standing on the moving platform in the configuration for induced anterior posterior sway (Anderson et al., 1977). One camera scans horizontally at the shoulder level while the other scans at the waist level. The cameras are situated on a specially constructed tripod so that they can easily be aligned at the proper levels for different subjects. The line scan camera measurements of waist and shoulder position are resolvable to the nearest 0.175 cm.

2.2 Stimulus Characteristics

The stimulus consisted of pseudorandom displacement stimuli which had been generated by signalling the velocity controlled platform with uniformly distributed pseudorandom noise that had been passed through a 0.2–2 Hz digital filter. These stimulus sequences were uniquely generated for each trial. Four peak velocities of motion stimuli were used: 12, 9, 6, and 3 cm/s.

2.3 Measured Variables

Through actively filtered A/D channels, twenty seconds of measurements for the shoulder, waist, and platform positions were sampled and stored on floppy discs at a rate of 25 Hz/channel. In the models derived, the measured platform position is the deterministic input time series while the measured shoulder and waist positions comprised the 2 output time series. Figure 1 illustrates the data of a typical pseudorandom trial of a subject with his eyes closed. In both eyes open and eyes closed

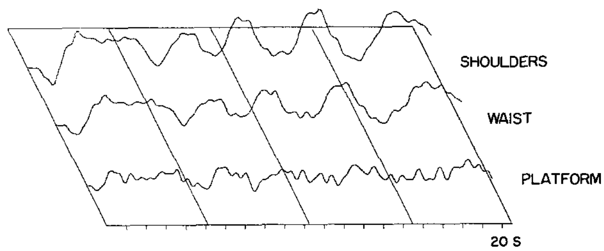

Fig. 1. A normal male subject's response tp a 12 cm/s peak amplitude 0.2–2 Hz pseudorandom input. The subject's eyes were closed during this trial

trials, the subjects' postural responses usually demonstrate a transient period of a few seconds in which the response characteristics were significantly changing, followed by a less variable steady state phase. These transient periods appeared to be longer in eyes closed trials. Only the steady state phase, the last 10 s (eyes closed) or the last 14 s (eyes open), was used in the data analysis.

2.4 Experimental Protocol

Prior to the experimental session, each subject was informed about the posture measurement system. Rest periods were provided at the beginning of a session as well as every 20 min throughout. The subject was instructed to stand with his/her stockinged feet at a 45° angle, heels together, head upright, arms comfortably folded across the chest and knees locked. Ear protectors were worn to minimize the effects of any background noise. The subject's eyes were either open and fixed upon a target at eye level or closed, depending on the requirements of the specific trial. Each session consisted of 21–20 s trials. These trials, randomly mixed by a computer program, were either static (no platform motion) or pseudorandom in nature.

2.5 Subjects

Six normal subjects in the age range of 19–25 years, who were determined by otoneurological examination to be free from abnormalities, were used in this study. Three of these subjects were male and three were female. Each subject was tested on five consecutive days under both eyes open and eyes closed conditions with the 4 peak velocity stimuli mentioned above. The 12, 9, and 6 cm/s trials were modeled so that a total of 180 trials from the six subjects comprised the data pool of the study. Since each trial consisted of both a waist and shoulder response, 360 parametric postural response models were derived.

3 Parametric Model

In choosing a model type, even for a black box process, several questions must be answered. A choice must be made between linear and nonlinear, discrete time and continuous time, time varying and time invariant, and deterministic and/or stochastic. Because of its complexity and adaptability, the posture control system was not expected to be a linear system. Previous work

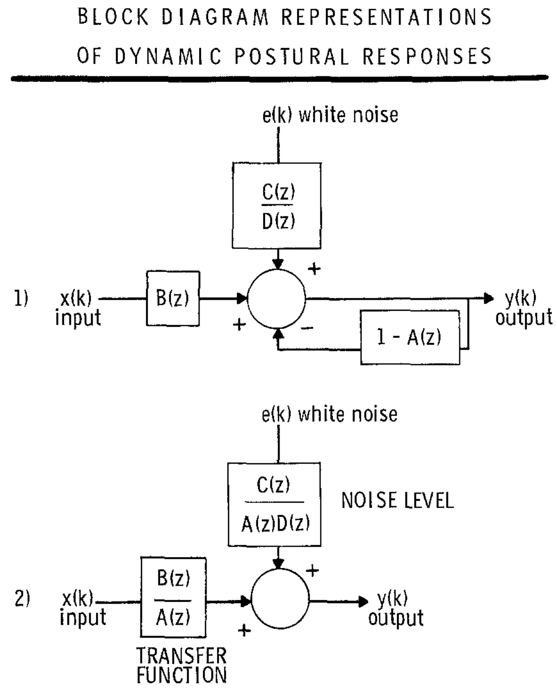

Fig. 2. Two interpretations for the transfer function pulse noise model combination. In the top of the figure, the noise is added at the input of the transfer function, whereas it is added to the output in the bottom diagram

suggests that it is not (Andres, 1979; Talbott, 1973). However, since individual responses to filtered pseudorandom noise demonstrated no obvious nonlinear behavior, a linear transfer function was assumed for the responses. The validity of this assumption is examined later. A discrete or difference equation model was convenient due to the sampled form of the data. For the steady state portions of the responses (Fig. 1), the parameters are assumed to be time invariant. Finally, in order to take into account the dynamic postural noise, a posture response is assumed to consist of a correlated noise portion as well as of a transfer function.

3.1 Model Type

The linear time invariant difference equation model below was postulated to be appropriate for the steady state portion of the pseudorandom responses. In this model, the output (measured waist or shoulder position) is expressed as a weighted sum of past outputs and past and present deterministic inputs (measured platform position):

$$y(k)=\sum_{l=1}^{L} a_l y(k-l) + \sum_{m=0}^{M} b_m x(k-d-m)+\varepsilon(k) \quad k=1,2,\ldots,N, \tag{3.1}$$

where $y(k)$, $k=1,2,\ldots,N$ is the output time series, $x(k)$, $k=1,2,\ldots,N$ is the input time series, N is the number of data points, d is the delay factor or deadtime, $\varepsilon(k)$, $k=1,2,\ldots,N$ is a correlated noise series, and L and M are the model orders.

Since the noise term, $\varepsilon(k)$, represents the postural sway noise and thus is correlated, it is modeled similarly to the postural responses:

$$\varepsilon(k)=\sum_{p=1}^{P} f_p\varepsilon(k-p) + \sum_{q=1}^{Q} c_q e(k-q)+e(k) \quad k=1,2,\ldots,N, \tag{3.2}$$

where P, Q are the model orders and $e(k)$, $k=1,2.\ldots,N$ is a stationary white noise series with zero mean and a covariance:

$$E[e(k)e(l)^T]=\Lambda\delta_{kl}. \tag{3.3}$$

The white noise series, $e(k)$, has an interpretation as the input to the physiological noise generation process, while the correlated noise, $\varepsilon(k)$, can be interpreted as the output of this process. However, from a practical point of view, any modeling or measurement errors are also included in the white noise series.

Since the data sequences of the above models are absolutely summable, these difference equations can equivalently be expressed with complex variables in the Z-plane where time delays are represented by the z^{-1} operator (Oppenheim and Schäfer, 1975; Papoulis, 1977). The Z-plane representation of the above postural model is:

$$Y(z)=\frac{z^{-d}B(z)}{A(z)}X(z)+\frac{C(z)}{F(z)A(z)}E(z), \tag{3.4}$$

where

$$A(z)=1+a_1z^{-1}+\ldots+a_lz^{-l}$$
$$B(z)=b_0+b_1z^{-1}+\ldots+b_Mz^{-M}$$
$$C(z)=1+c_1z^{-1}+\ldots+c_Qz^{-Q}$$
$$F(z)=1+f_1z^{-1}+\ldots+f_Pz^{-P}.$$

In this form it is easily seen to have a transfer function component and a noise model component. Two interpretations for the model are provided in Fig. 2. If expressed in the form shown in the top of Fig. 2, with the noise as an input, the model is in convenient form for the parameter estimator. The bottom representation of Fig. 2 is more suitable for physiological interpretations.

The frequency response of a transfer function or noise model can be determined directly by evaluating the transform at $z=e^{j\omega}$, $\omega=0,\ldots,\pi$ (Oppenheim and

Schäfer, 1975; Papoulis, 1977):

$$pf(e^{-j\omega}) = \frac{b_0 + b_1 e^{-j\omega} + \ldots + b_m e^{-j\omega M}}{1 + a_1 e^{-j\omega} + \ldots + a_n e^{-j\omega N}}. \tag{3.5}$$

Alternatively, one can examine the locations in the Z-plane of the singular points of the numerator polynomials, $B(z)$ and $C(z)$ (zeros), and of the denominator polynomials, $A(z)$ and $F(z)$ (poles) (Oppenheim and Schäfer, 1975). With the exception of a gain factor, such a pole-zero plot completely represents a system.

The frequency responses of the parametric postural models were determined with both methods above in order to select features of the models for statistical analysis. These selected features are listed below.

a) Model orders. The model orders consist of the number of poles and zeros in both the noise model and transfer function as well as the deadtime factor.

b) Pole, zero locations. The pole and zero locations for both the noise model and transfer function provide information about spectral shape and frequency and damping characteristics, respectively.

c) Gain, phase, and transfer function variance. From the parametric transfer function's frequency response, a low frequency (0.2 Hz) gain and a relatively high frequency (1.4 Hz) phase lag were examined. The parametric transfer function was integrated to provide an estimate of the transfer function variance.

$$\mathrm{Sig} = [pf(e^{-j\omega})]^2 [X(e^{-j\omega})]^2, \tag{3.6}$$

where $pf(e^{-j\omega})$ is calculated as in (3.5) and $[X(e^{-j\omega})]^2$ is the input spectrum calculated nonparametrically.

d) Noise variance. The noise spectrum was integrated to provide an estimate of the noise variance or the amount of the postural noise

$$\mathrm{Noise} = [C(e^{-j\omega})/(F(e^{-j\omega})A(e^{-j\omega}))]^2 \,\mathrm{Var}_e, \tag{3.7}$$

where Var_e is the residual variance.

e) Residual variance. The residual variance provided an estimate of the amount of white noise which was input to the physiological noise generation process (see Fig. 2).

Where possible, the postural response model features were subjected to a repeated measures ANOVA analysis (Winer, 1971) in order to determine statistically significant effects due to the day of testing, the size of the input signal, or the presence or absence of vision.

3.2 Parameter Estimation

Before being subjected to the parameter estimation procedure, the platform position, waist, and shoulder data were detrended in order to meet the stationarity requirement. In practice, the input series was already quite stationary. Detrending instead of differencing (Box and Jenkins, 1976) was chosen in order to avoid the high pass filtering effect and subsequent increase of the noise to signal ratio caused by the differencing operation.

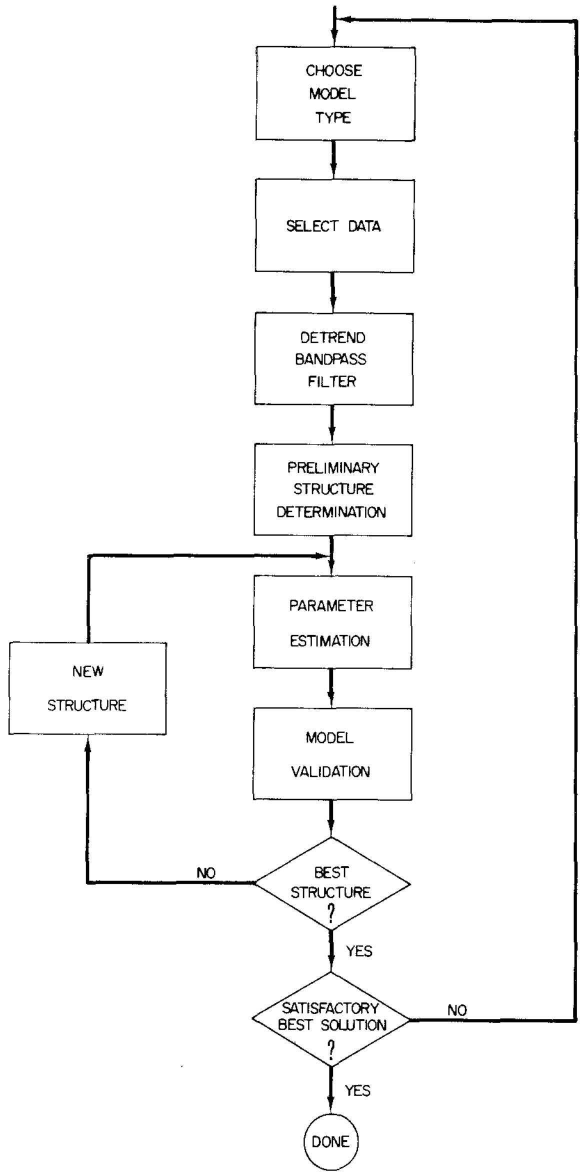

Fig. 3. Block diagram of parametric identification methodology

The parameter estimation scheme chosen is a version of the extended Kalman Filter (Werness and Anderson, 1984). This estimator provides for the estimation of an arbitrary noise model as well as a transfer function. It can be shown that the parameter estimates converge asymptotically to a stationary point of the same loss function used in maximum likelihood (Panuska, 1980; Ljung, 1977) and thus are asymptotically unbiased and efficient.

3.3 Model Selection

As Fig. 3 indicates, the empirical selection of model orders is an iterative procedure. In this approach, a

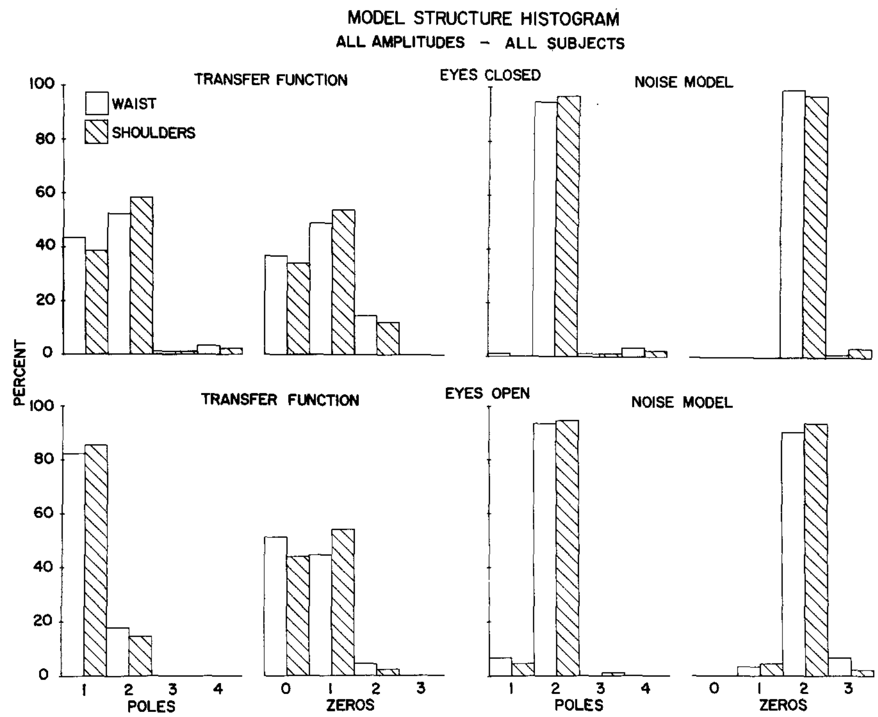

Fig. 4. Model structure histogram. All subjects and input amplitudes are represented

model structure is assumed, and the parameters are estimated. The resulting model is evaluated and if found to be unsatisfactory, a new model structure must be postulated and fitted. The main objective of the model selection procedure was to select a parametric postural response model that was as parsimonious as possible but adequately represented the data. Evaluation criteria used are detailed in Werness and Anderson (1984). They are briefly noted below:

1. The residuals [also estimates of the white noise series, $e(k)$] should contain no remaining information about the model and hence should be "white" or an uncorrelated series. The residuals should also be uncorrelated with a "whitened" version of the input series. Lastly, the residuals of the chosen model should be smaller than other satisfactory models.

2. Near cancellations or small magnitude of poles and zeros indicated overparametrization.

3. The frequency response of the parametric model evaluated from (3.5) should ressemble those calculated nonparametrically (Werness and Anderson, 1984).

4 Transfer Functions

4.1 Structure

A major result of this study is that low order models are sufficient to describe the postural responses (Fig. 4). Only a few transfer functions require more than two poles or more than one zero. Most of the transfer function poles fall near the 0 Hz unit radius position on the unit circle in the Z-plane (Fig. 5), although a few occurred at about 1 and 12.5 Hz and are not shown in the figure. Poles near this 0 Hz position on the unit circle indicate an integration. It can be seen in this figure as well as in the model structure histogram, that more eyes closed transfer functions than eyes open ones exhibit complex poles, although it was difficult to test this phenomenon statistically. These complex poles are closer to the unit circle corresponding to the fact that the responses are more oscillatory and less damped in the eyes closed case.

Most of the transfer function zeros are real, occurring near the unit radius, 0 Hz position, the differencing (for zeros) position, on the unit circle (Fig. 6). Transfer functions which have these zeros indicate a response more to platform velocity than to platform position. Since this figure as well as the model structure histogram indicate that these zeros are present more frequently in the eyes closed condition, it appears that subjects without vision respond more frequently to the velocity of the platform.

Figure 6 suggests another basic difference between responses with and without vision: the zeros from the eyes closed transfer functions tend to cluster just inside the unit circle whereas those from the eyes open ones tend to cluster just outside the unit circle for both the waist and shoulders, although this difference was significant (<0.01 level) for only the shoulders. Trans-

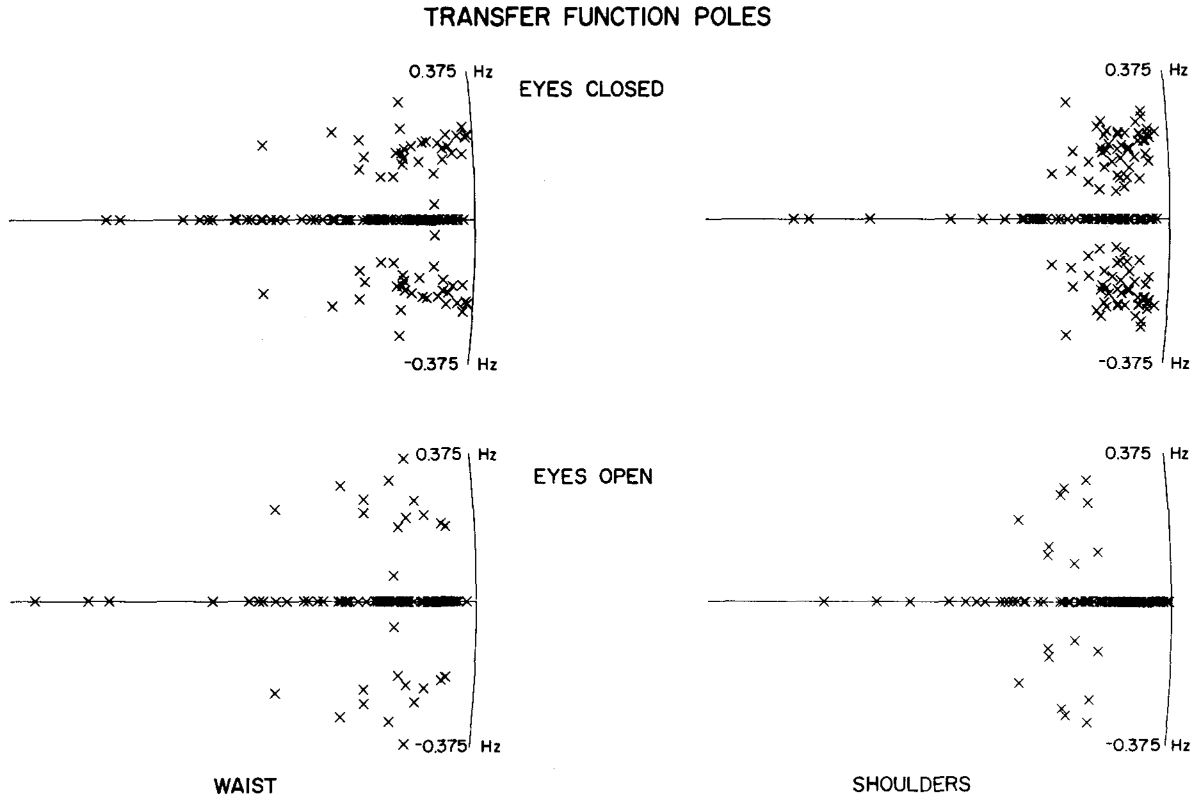

Fig. 5. Transfer function pole locations in the Z-plane. All subjects and input amplitudes are represented, but only arcs of the unit circle extending from $+0.375$ Hz to -0.375 Hz are shown

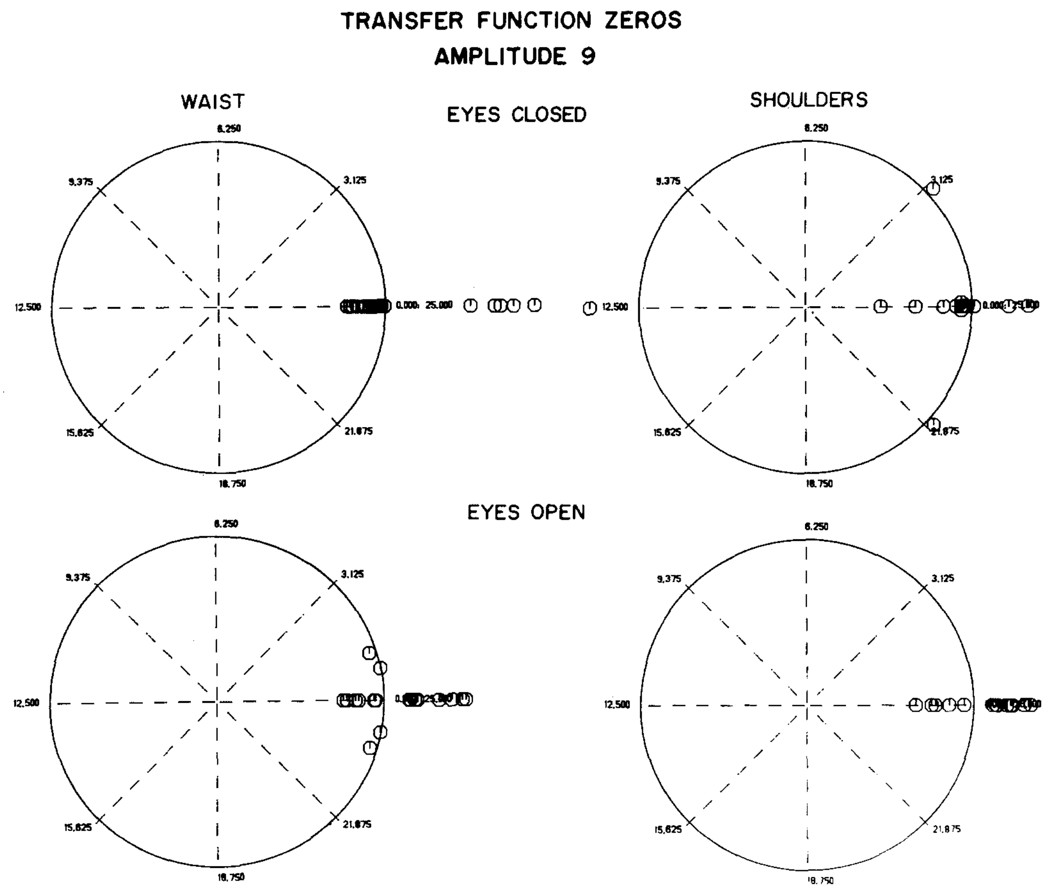

Fig. 6. Locations of transfer function zeros in the Z-plane for the input amplitude of 9 cm/s. All subjects are represented

Output phase lag versus input amplitude

Amplitude	Eyes closed				Eyes open			
	Waist		Shoulders		Waist		Shoulders	
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
6	2.84	0.30	3.66	0.29	2.94	0.78	4.24	0.48
9	2.75	0.33	3.52	0.35	2.90	0.54	4.01	0.48
12	2.70	0.28	3.46	0.36	3.10	0.58	4.01	0.33

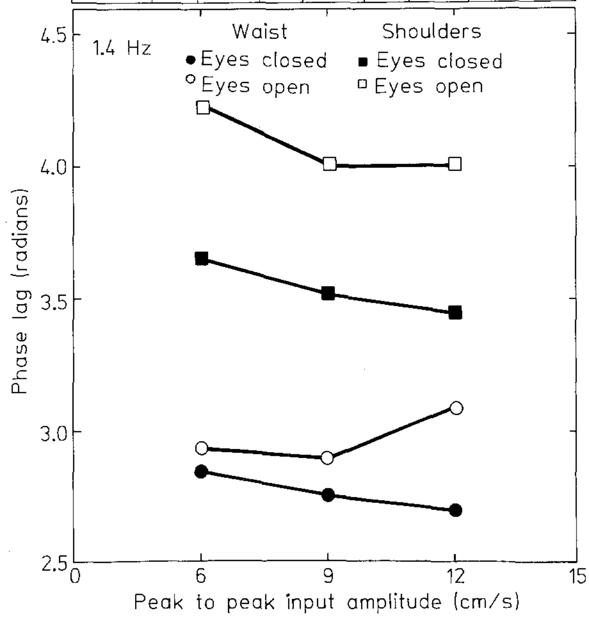

Fig. 7. 1.4 Hz transfer function phase lags for all subjects

Output gain versus input amplitude

Amplitude	Eyes closed				Eyes open			
	Waist		Shoulders		Waist		Shoulders	
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
6	2.25	1.17	2.81	1.72	0.55	0.28	0.61	0.31
9	1.91	0.68	2.28	0.85	0.59	0.30	0.66	0.29
12	1.61	0.44	2.15	0.71	0.56	0.30	0.57	0.30

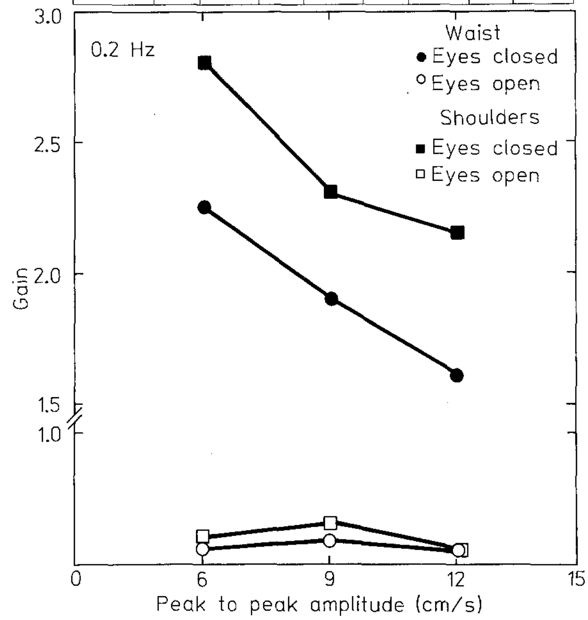

Fig. 8. 0.2 Hz transfer function gains for all subjects

fer functions containing zeros outside the unit circle are nonminimum phase systems, which have been shown to have larger phase lags and lower energy responses to the same input than minimum phase systems (Papoulis, 1977). Thus, the transfer function zero locations suggest that the responses are slower and more energy minimizing in the eyes open case.

There are some noteworthy things about the 1.4 Hz phase lags and 0.2 Hz gains derived from the parametric transfer functions. It is evident from Fig. 7, and not surprising in light of the previous discussion of nonminimum phase systems, that the eyes open phase lags are greater than the eyes closed ones. Again, this dichotomy is highly significant only for the shoulders ($p=0.0003$). Also, the shoulder phase lags are greater than those of the waist, thus indicating that significant postural response motion is occurring at the waist as well as the ankles. These phase lags include the effect of any deadtime. The deadtimes were shown in the ANOVA analysis to be independent of the day of testing, the input amplitude, as well as the eyes open/closed factor. For the waist, the mean deadtime is 0.17 ± 0.10 s, whereas for the shoulders, it was 0.25 ± 0.10 s. There are highly significant gaps ($p=0.0002$) between the eyes closed gains and eyes open gains, the eyes closed gains being much greater (Fig. 8). Interestingly, there are almost no differences between the eyes open waist and shoulder gains, again evincing evidence of much postural response motion occurring at the waist. In contrast, the shoulder gains greatly exceed the waist gains in the responses without vision. Also observable in the figure is a tendency for the eyes closed gains to exhibit the nonlinear effect of decreasing with an increase in input amplitude. This tendency was significant for the waist (prob$=0.0076$) but not for the shoulders (prob$=0.2362$).

This suggested nonlinearity may be a slew rate phenomenon: at the faster input amplitudes, the biomechanical characteristics of the subjects prevent them from fully keeping up with the platform excursions. The limitation that arises when a linear systems approach such as this parametric technique is used to model a nonlinear system is that derived models are only for the specific input used in their derivation and thus can't be used to predict responses to other inputs. However, the linear system approach with its interpretational and computational advantages can be used to describe responses for a given specific input.

4.2 Transfer Function Summary

The features of the parametric transfer functions provide for easy classification of the responses. That speed of response is more evident in the eyes closed condition is indicated by the reduced phase lags, the more frequent occurence of minimum phase zeros, and of complex poles with radii close to 1 indicating underdamped second order responses in the eyes closed condition. The more frequent occurrence of zeros near the 0 Hz unit radius position in eyes closed responses suggests that the anticipatory nature of knowledge of the platform's velocity is more valuable in responses without vision.

On the other hand, several of these parametric model features indicate that minimization of energy expenditure, particularly with respect to motion of the head and shoulders, is a significant aspect of the responses with vision. The smaller low frequency gains, particularly for the shoulders, and the presence of real poles and complex poles with smaller radii indicate more damped and less oscillatory responses in the eyes open case. Furthermore, the nonminimum phase zeros, which are associated with eyes open responses, may have an energy minimization interpretation.

The observed effects of vision on the parametric model results described here could be interpreted in several ways. One such interpretation is that the postural goal in the eyes closed situation is to maintain center of gravity stability by quick responses to the platform's motion, whereas the postural goal with vision seems to be minimization of energy expenditure, especially of shoulder and head movement at the cost of a slower response. Another interpretation offered by Talbott and Brookhart (1980) is that, with eyes closed, a subject minimizes the error between the platform's and his own motion, whereas with eyes open, he minimizes the error with respect to a stationary surround. Yet another possible interpretation is that vision supplies feedback stabilization to a relatively unstable open loop system (Dichgans et al., 1976; Diener et al., 1982).

4.3 Comparison to Other Studies

The parametric transfer function features described here can be used to facilitate a comparison of these concise representations of dynamic postural responses with transfer functions derived with other methods. The damping effect of vision on postural motion has been previously demonstrated by many in both static situations (Taguchi et al., 1978; Hufschmidt et al., 1980) and dynamic ones, including responses of dogs to both predictable (Talbott, 1974) and unpredictable (Talbott and Brookhart, 1980) stimuli, and responses of humans to predictable (Andres, 1979) and unpredictable stimuli (Ishida and Imai, 1980; Diener et al., 1982).

Closer comparisons between these parametric transfer functions derived with 0.2–2 Hz pseudorandom noise velocity inputs must be made with other postural transfer functions with care. Different control strategies are expected with a predictable stimulus such as a sinusoid than with an unpredictable one (Stark, 1968). Few other dynamic posture studies have employed random inputs. Meyer and Blum (1977) utilized a rotating platform and derived nonparametric transfer functions between platform position and position of the center of gravity of human subjects. Their platform inputs were small amplitude pseudorandom noise between 0 and 1 Hz. Their illustrated low pass type transfer function is characterized by a low frequency gain of about 0.6 and a phase lag at 1 Hz of about π radians. These results appear very close to the average waist gain of 0.57 and the average 1.4 Hz phase lag of 2.98 radians found here in the eyes open case. In studies on dogs, Talbott and Brookhart (1980) used an unpredictable stimulus consisting of a weighted sum of 7 sinusoids, up to 2 Hz with the highest frequency sinusoid having the smallest amplitude. Their transfer functions of the dog position with respect to the platform position were derived nonparametrically and then fitted with models containing 1 or 2 poles and some deadtime, and thus are in good agreement with these parametric transfer functions for humans.

The parametric transfer function results here are at variance with those presented by Ishida and Imai (1980). They calculated transfer functions with platform acceleration as input and ankle joint moment and the angles of the waist and shoulders with respect to the vertical as output. Their waist and shoulder angle transfer functions show 180° or less phase lag with respect to platform acceleration (waist angle $= -90°$ and shoulder angle $= -180°$) at 1.4 Hz. These phase lags imply that their subjects were keeping up with or leading the motion of the platform. These are very small phase lags, even for predictable stimuli (Diener et al., 1982; Gantchev and Popov, 1973).

5 Noise Models

5.1 Structure

The noise models, assumed to be output noise models (part *b* of Fig. 2), consist usually of 2 poles and 2 zeros (Fig. 4). Since the transfer function poles are shared with the noise model, the distribution of noise model pole locations in the Z-plane differed from that of the transfer function poles by the addition of a few poles on the real axis. Noise model zeros are usually complex with radii in the range of 0.6–0.8 and with frequencies

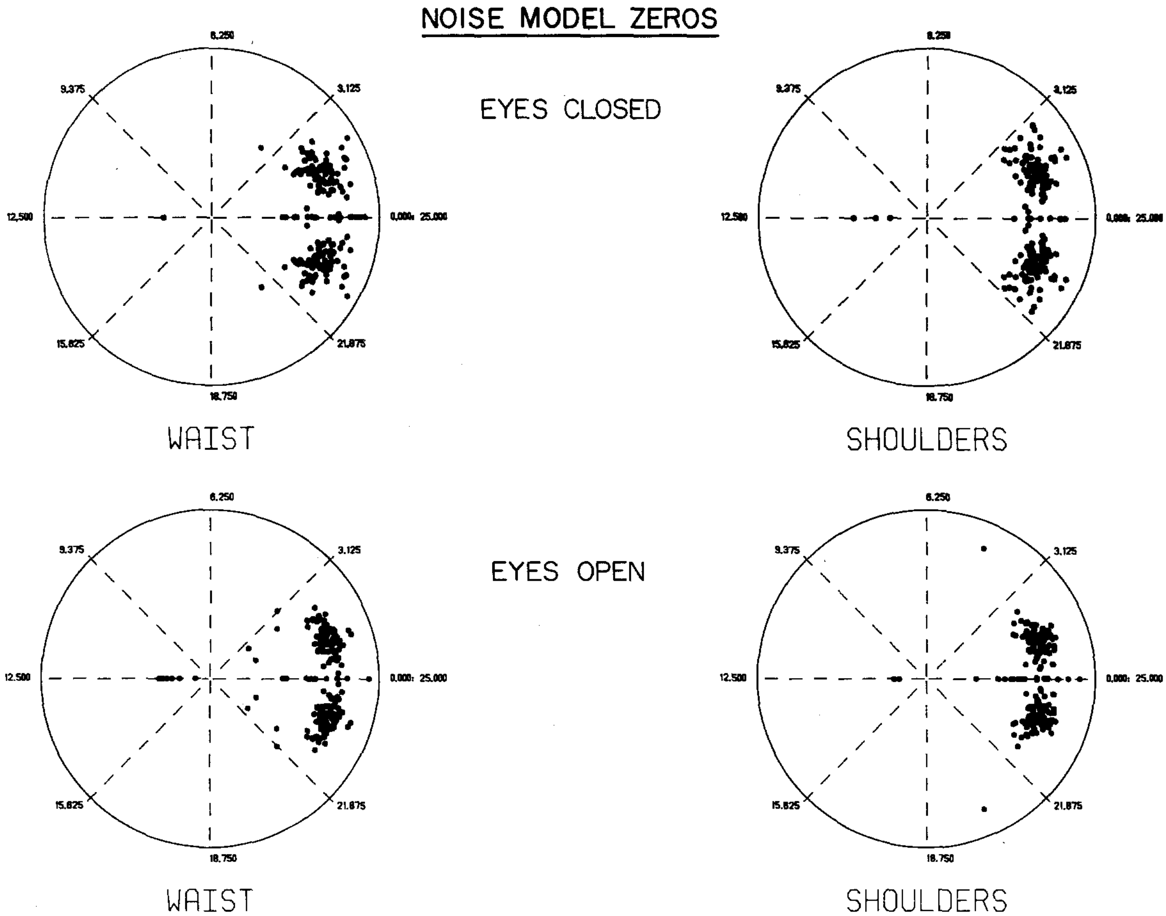

Fig. 9. Locations of noise model zeros in the Z-plane for all subjects and input amplitudes

Table 1. ANOVA p values

Dependent variable	Independent factors			
	Waist		Shoulders	
	Eyes	Amplitude	Eyes	Amplitude
Noise variance	0.002	0.0009	0.0093	0.0034
Residual variance	0.0006	0.0001	0.0072	0.0002
Noise zero frequencies	0.0614	0.0018	0.0169	0.0293
Noise variance (recalculated with a constant residual variance)	0.0036	0.0022	0.0127	0.0107

around 1–2 Hz (Fig. 9). There is an interesting correlation between their frequencies and input amplitude. As input amplitude increases from 6 to 12 cm/s, these frequencies increase from near 1 Hz to near 2 Hz. Also, these frequencies are larger for the eyes closed responses (see Table 1).

The noise model, repeatedly characterized by the presence of two poles relatively close to the unit circle at or near 0 Hz and two zeros with relatively small radii between 1 and 2 Hz, has a lowpass filtering effect in the frequency domain. Specifically, most of the noise model's energy concentrates near 0 Hz and tapers off as

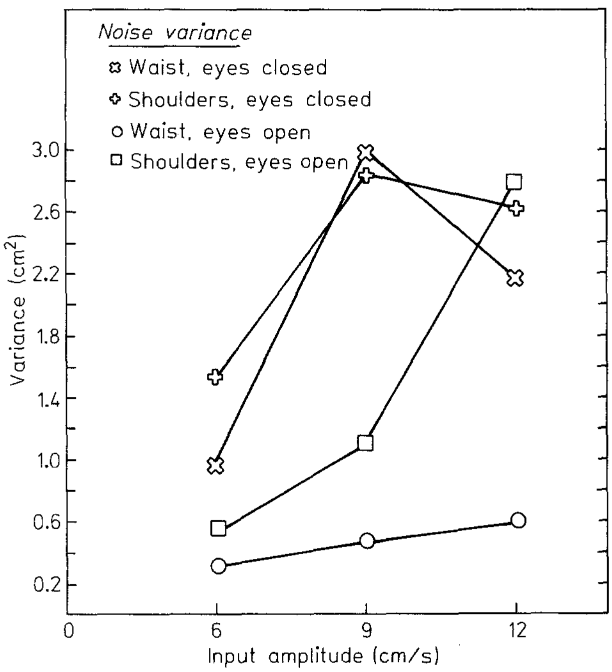

Fig. 10. Noise variance for all subjects

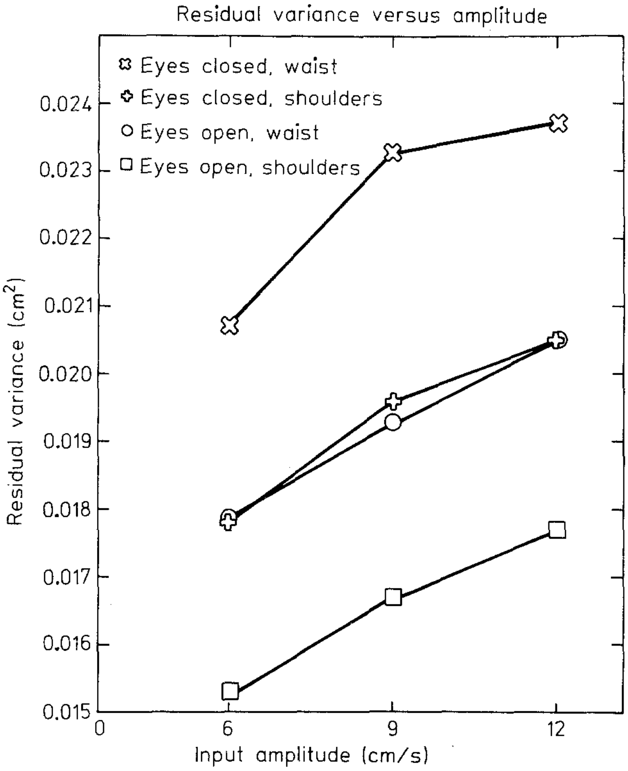

Fig. 11. Residual variances for all subjects

frequency increases. The presence of the zeros serves to increase the cutoff rate of the energy at higher frequencies. From the time domain point of view, Box and Jenkins (1976) point out that a time series model with two poles very close to the unit circle is capable of generating linear trends. Thus, the noise model may consist of very low frequency oscillations and much drifting. This characterization of postural noise in a dynamic situation is consistent with previous characterizations from this laboratory of static postural sway noise as very lowpass (Andres, 1979) as well as the low frequency characterizations of static sway from other laboratories (Aggashyan, 1972; Brauer and Seidel, 1978).

5.2 Noise Variance

The noise variance (3.7) is found to be positively correlated in a nearly linear manner with input amplitude as well as greater in the no vision condition responses (Fig. 10). Further ANOVA analyses showed these amplitude and visual condition effects to be partially caused by the tendency of the noise model zero frequencies, and thus the frequency range of the noise spectrum, to increase with input amplitude and eye closure. The input noise series or residuals, whose variance demonstrates both amplitude and visual condition effects (Fig. 11), are also obvious contributors to these same observations in the noise variance (Table 1).

Since the residuals contain any modeling errors and measurement noise as well as the input noise series, the possibility that these other residual components contribute to the observed effects on the residual variance was examined. Examination of the autocorrelation statistics of the parametric postural response models indicated that residual whiteness and thus model adequacy (including any nonlinearity problems) was not related to either input amplitude or eye condition. In addition, a set of calibration experiments with a rigid pole as the "subject" ruled out the possibility that the digital line scan camera quantization noise might increase with either increasing platform velocity or increasing motion of the target from the center position of the cameras. Thus, it is probable that the amplitude and visual condition effects of both the noise variance and the component input noise series variance have physiological origins.

5.3 Noise Model Discussion

Noise is frequently present in biological systems. Dependency of noise power on input amplitude is also a frequent observation in physiological systems. For example, Stark (1968) demonstrated that the amplitude of pupil noise was linearly related to input light intensity and incorporated this characteristic into his model of pupillary response by treating it as a multiplicative noise factor. In addition, physiological tremor amplitude is widely known to be a function of the amount of muscle force (Joyce and Rack, 1974; Marsden, 1978; Matthews and Muir, 1980). Similarly, the noise which exists in the posture system exhibits a dependence upon input amplitude. Since over a steady state period of a response, the quantity of posture noise (noise variance) is a constant, it is not suitable to model it as a multiplicative factor.

Postural noise, since it is an immediate consequence of muscle activity, could be considered to be a special case of physiological tremor. Although many theories of its cause have been put forward, no single explanation covers all the features of physiological tremor (Marsden, 1978). A major reason for this difficulty is that the oscillation of any mechanical system, such as the human body or limb, is a function of both the inherent mechanical properties of the system combined with the drive on the system. Consider the following differential equation of a mass-spring system:

$$mx'' + cx' + kx = 0\,, \tag{5.1}$$

and the corresponding quadratic formula for the roots of such a system:

$$x = -c/2m +/-(4mk - c^2)^{1/2}/2m\,, \tag{5.2}$$

where m is mass, c is the damping constant, and k is the spring stiffness. For example, natural mechanical resonance has been identified for elbows and fingers since its frequency decreases with added mass and increases with added stiffness (Marsden, 1978). In addition to their natural frequencies, these limbs exhibit another tremor component at 10–12 Hz, whose frequency is unaffected by added mass or load, but whose amplitude is affected by muscle force and is thus probably not due to passive mechanical factors.

Similarly to demonstrated physiological tremors, the noise characteristics here may be a reflection of the mechanical properties of the human plant, which may be viewed as a complex array of mass-spring systems. The very low frequency character of both static postural sway noise and the dynamic postural noise (and transfer function) examined in this study is a reflection of the relatively large mass of the human body. The observation that the low frequency dynamic postural sway noise extends its bandwidth when the input amplitude increases by virtue of the result that the frequencies at which the noise model zeros increased, may indicate that muscle stiffness intensifies with input amplitude. Investigators have previously emphasized the role of muscle stiffness in postural regulation (Grillner, 1972). Gurfinkel et al. (1974) calculated stiffness of the ankles during human stance and concluded that the observed levels of stiffness were sufficient to stabilize the human body modeled as an inverted pendulum during small sway deviations. Furthermore, evidence has been presented that muscle stiffness is a regulated parameter of the central nervous system in motor control mechanisms (Kelso and Holt, 1980). An increase in stretch reflex activity could be responsible for an intensification of muscle stiffness (Houk, 1979). Possibly muscle stiffness is being augmented in order to meet the higher demands of the larger input amplitudes. Another possible mechanical factor causing a higher frequency vibration of a passive mechanical system is a reduced damping factor. Active control strategies could also be involved.

6 Conclusion

Parametric black box models with a transfer function and a noise component of the human postural system have been empirically derived from output shoulder and waist position responses to an input position of a platform moved in a linear anterior-posterior direction via bandlimited pseudorandom velocity commands. The resulting model orders are quite small so that statistical comparisons are easily made with the locations of the models' poles and zeros as well as with other derived features. Also, the ANOVA analyses of all the model features revealed that postural responses did not reveal a day by day learning effect. This facility for classification of large numbers of postural responses to dynamic inputs with both transfer function and noise information will be useful for developing clinical diagnostic criteria and in augmenting understanding of postural control.

The parametric transfer functions are similar to others derived nonparametrically from responses to random inputs. The transfer function features also confirm the damping effects of vision on postural stability that have been described at least since Romberg.

For the first time, dynamic postural sway noise has been quantified along with deterministic responses to random inputs. Dynamic noise spectra are low pass in character, similarly to those of static postural noise. The quantity of noise variance was positively related to the deterministic input amplitude and was greater for the eyes closed responses. These variations were seen to be contributions of both similar behavior of the input white noise to the noise model (see Fig. 2), and of the amplitude dependent locations of the noise model zeros. This input amplitude dependency of the quantity of noise is analogous to other physiological situations.

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