Review

# Selection of perturbation parameters for identification of the posture-control system

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**Abstract**—*Postural perturbations are often used in experimental investigations of human balance and postural control. Treating the perturbation as the input and the resulting postural sway response as the output, an input/output model of the posture-control system can be identified. Selection of the perturbation parameters can have a substantial influence on the accuracy of the identification and on the interpretation of the results. Pertinent parameters include type of perturbation, waveform, power spectrum, bandwidth, amplitude and test duration. The selection of these parameters is discussed in the light of general requirements for persistent excitation, accurate identification, stationarity and subject safety. Experimental results are used to illustrate specific issues.*

**Keywords**—*Balance, Posture, Sway, System identification*

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## 1 Introduction

Postural perturbations are often used in experimental investigations of human balance and postural control. Typically, the subject stands on a moving platform and the resulting postural sway is measured. The postural sway may be characterised in terms of

(*a*) motion of certain body segments or joints
(*b*) joint moments
(*c*) electromyographic activity in various muscle groups
(*d*) displacement of the centre of pressure on the feet.

Many investigators have studied the spontaneous postural sway of subjects as they stand quietly on a stationary floor (Terekhov, 1976). Spontaneous sway measurements quantify an output of the posture-control system but fail to characterise the input which caused the sway to occur. As a result, the system itself cannot be identified and no inferences or predictions can be made regarding the performance of the system under different test conditions or its response to destabilising perturbations. To make these predictions an input/output model must be identified.

An input/output model of the posture-control system can be identified by applying measurable postural perturbations to the subject. The perturbation is treated as the input to the model and the postural sway response is the output.

The particular perturbation signal used in an experiment may have a substantial influence on the accuracy of the system identification and on the interpretation of the results. A wide variety of different perturbation signals have been used by various investigators, as shown in Table 1. Andres and Anderson (1980) pointed out the need for accurate quantification of perturbation signals; however, the criteria by which perturbation parameters are selected have not been adequately addressed in the literature.

The purpose of this review is to discuss the selection of perturbation parameters for use in posture-control experiments. After a description of some general requirements for system identification, the selection of appropriate perturbation parameters is discussed in light of these requirements. Experimental results are then used to illustrate some of the specific issues.

It is assumed that the purpose of the posture-control experiment is system identification, with the aim of predicting balance performance in 'daily life' situations on the basis of laboratory tests. It is also assumed that the goal is a linear, time-invariant model. Linear analysis has a tremendous advantage over nonlinear methods in terms of computational simplicity and ease of interpretation. Although linear time-invariant models are a gross simplification of the true posture-control system, these models can often provide useful results when applied over a limited range of input amplitudes and a limited time period.

## 2 General requirements

### 2.1 *Persistent excitation*

A minimum requirement for system identification is that the input signal 'persistently excites' the dynamics of the

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*Table 1 Perturbation parameters used by other investigators*

| Investigator(s) | Type of motion | Position waveform | Power spectrum | Frequency range, Hz | Amplitude | Duration |
|---|---|---|---|---|---|---|
| | Perturbation parameters | | | | | |
| HONJO and FURUKAWA, 1957 | rot (ap) | ramp? | N/A | N/A | 4–20° s$^{-1}$ | N/A |
| NASHNER, 1971; 1976; 1977 | rot (ap) | ramp? | N/A | N/A | 0·15–6° s$^{-1}$ | N/A |
| | tra (ap) | ramp? | N/A | N/A | 0–5 in s$^{-1}$ | N/A |
| GANTCHEV *et al.*, 1972; | rot (ap) | sine | N/A | 0·2–1·0 | 3° | ? |
| GANTCHEV and POPOV, 1973 | tra (ap) | sine | N/A | 0·2–1·4 | 36 mm | ? |
| LITVINTSEV, 1973 | tra (ap, ml) | ramp? | N/A | N/A | ? | N/A |
| WALSH, 1973 | rot (ap, ml) | sine | N/A | 0·06–0·7 | 0·3° | 20 s |
| GURFINKEL *et al.*, 1976 | tra (ap) | sine | N/A | 0·2–2·0 | 5 cm | 40 cycles |
| | rot (ap) | sine | N/A | 0·2–2·0 | 1, 2° | 40 cycles |
| | | ramp | N/A | N/A | 0·1–0·2°, 0·6° s$^{-1}$ | N/A |
| MEYER and BLUM, 1978 | rot (ap) | sine | N/A | 0·1–1·0 | ? | 160 s |
| | | random | ? | ?–1·0 | 0·5° max | 160 s |
| | | ramp | N/A | N/A | 0·6°, 15° s$^{-1}$ | N/A |
| ALLUM and BUDINGEN, 1979 | rot (ap) | ramp | N/A | N/A | 1–4°, 30–50° s$^{-1}$ | N/A |
| NASHNER *et al.*, 1979; | rot (ap) | half-sine | N/A | 2, 4 | 5°, 20° s$^{-1}$ | N/A |
| NASHNER, 1980; | tra (ap) | half-sine | N/A | 2, 4 | 8 cm, 30 cm s$^{-1}$ | N/A |
| NASHNER and CORDO, 1981 | tra (vt) | half-sine | N/A | 2, 4 | 5 cm, 20 cm s$^{-1}$ | N/A |
| HIBINO, 1980 | rot (ap) | sine | N/A | 0·1–3·0 | 5° | ? |
| ISHIDA and IMAI, 1980 | tra (ap) | binary-PRN | bell-shaped | 0·2–2·0 | ? | ? |
| ANDRES, 1982 | tra (ap) | ramp | N/A | N/A | 7·5 cm s$^{-1}$ | N/A |
| | | sine | N/A | 0·2–0·8 | 6–18 cm s$^{-1}$ | 20 s |
| | | PRN | ? | 0·1–2·0 | 4–10 cm s$^{-1}$ max | 20 s |
| DIENER *et al.*, 1984 | rot (ap) | ramp | N/A | N/A | 2–8°, 10–100° s$^{-1}$ | N/A |
| TOKITA *et al.*, 1984 | tra (ap) | PRN | ? | 0·1–5·0 | 10 cm max | ? |

rot = rotational, tra = translational, ap = anterior-posterior, ml = medial-lateral, vt = vertical, PRN = pseudorandom noise, N/A = not applicable

system over the measurement period (ISERMANN, 1980). This means that the frequency content of the input must exercise the system over the range of frequencies for which the model is needed.

### 2.2 *Accuracy of identification*

Selection of appropriate input (i.e. perturbation) parameters can help to minimise random error and bias in the model estimates. In fact, it is possible to design optimal input signals that minimise model errors, given constraints on the measurement time, the sampling rate and the amplitude and power characteristics of the input and output signals (GOODWIN and PAYNE, 1977). However, in general, the design of truly optimal input signals requires detailed prior knowledge of the system model and noise characteristics (BOX and JENKINS, 1976), information which is generally not available *a priori.*

### 2.3 *Stationarity*

Identification of a time-invariant model requires that the characteristics of the system do not change over the measurement period, i.e. the system must be stationary. In studying the posture-control system, there are at least three factors that could influence stationarity:

(*a*) adaptation to the perturbation stimulus
(*b*) adaptation to the test environment
(*c*) fatigue.

To minimise adaptation, the test perturbation must be unpredictable. Changes in anxiety level may influence postural responses, as subjects gain familiarity with the test environment. Fatigue will become a factor if the duration of the test is excessively long.

### 2.4 *Human tolerance*

The test perturbation must be safe, i.e. the risk of falling must be minimised. The subjects' perception of the risk must also be minimised, since subject apprehension could result in changes in the response strategy. For example, subjects might 'brace' themselves through increased co-contraction of antagonist muscle groups. Discomfort is another factor that could influence the response. High-frequency vibration can induce discomfort, as can excessively long measurement periods.

## 3 Perturbation parameters

### 3.1 *Type of perturbation*

For a perfect linear system the system identification is independent of the nature of the input. However, the posture-control system is not perfectly linear and extrapolation of experimental test results to actual balance and falling behaviour depends on the degree to which the test perturbation simulates common causes of falling, such as slips, trips and mis-steps. To allow such extrapolation the test perturbation should simulate a typical falling circumstance in terms of

(*a*) kinematics, i.e. the relative motion of the body segments
(*b*) sensory imput, i.e. the visual, vestibular, proprioceptive and exteroceptive sensory cues.

Postural perturbations can be applied easily and in a controlled manner by moving a platform on which the subject stands. By restricting the number of degrees of freedom of the perturbation motion it may be possible to reduce the complexity of the posture-control model.

Horizontal platform translation simulates the kinematics of a slip, trip or mis-step in that there is a relative acceleration between the feet and the upper body. Provided that the visual field moves with the platform, the dominant sensory cues are consistent with a fall relative to the platform frame of reference. The one inconsistency lies in the utricular otoliths, which record the linear acceleration of the head in an absolute reference frame. Because of the low frequency response of the otoliths (NASHNER, 1971) and the otolith reflexes (ANDERSON *et al.*, 1977) to horizontal accelerations, this inconsistency should have relatively little effect on dynamic balancing responses.

Platform rotation might simulate overstepping a curb or stairway tread, but otherwise does not simulate the kinematics of typical falls. Furthermore, the resulting sensory cues may be inconsistent. For example, a 'toes-up' platform rotation induces a backwards falling motion yet results in ankle dorsiflexion, yielding proprioceptive cues consistent with a forward fall. The resulting stretch reflexes act to further destabilise the body (DIENER *et al.*, 1984).

In an ideal simulation of a slip, trip or mis-step, the perturbation would be applied to the supporting foot during gait, an approach used by NASHNER (1980). However, as discussed in Section 3.2, a continuous waveform may be desired, in which case the one-foot perturbation becomes impractical.

### 3.2 *Waveform*

Transient waveforms (e.g. step change in platform acceleration) provide the best simulation of sudden slips or trips; however, they also present several difficulties. The most serious problem relates to the risk of injury to the experimental subjects, which is of particular concern in testing the elderly. Even if the risk of injury is reduced through the use of a safety harness, handrails or padded surfaces, subject apprehension may influence the balance response.

To achieve accurate identification of 'noisy' systems using transient waveforms, the test must be repeated many times and the results averaged (RAKE, 1980). However, repetitive testing with the same transient waveform can lead to adaptive changes in the response (NASHNER, 1976), thereby degrading identification of a time-invariant model. This problem may be overcome to some degree by randomising the time of onset of the perturbation and by randomly varying the amplitude and/or direction of the perturbation.

The use of transient waveforms may lead to reduced linearity in the measured sway response. Since the transient input must have a relatively large amplitude to achieve acceptable signal-to-noise in the measurements, it is more likely to excite saturation-type nonlinearities in the posture-control system.

The use of continuous waveforms can circumvent many of the difficulties inherent to the use of transient waveforms. Through appropriate choice of amplitude, power spectrum and bandwidth, a continuous perturbation can be designed so as to minimise apprehension and risk of falling. If the waveform is unpredictable to the subject then the test should elicit posture-control system behaviour similar to that occurring in an actual slip, trip or mis-step.

Sinusoidal inputs have the disadvantage of predictability (STARK, 1968). Subjects are able to adapt to this type of perturbation, and may learn to 'ride' the platform (ANDRES, 1982). As a result, the measured response may not be indicative of the response in typical falling situations. Use of sinusoidal waveforms has the further disadvantage of being time-consuming, since each frequency within the range of interest must be tested separately.

To circumvent the problems of learning and adaptation, the perturbation must be made unpredictable. This can be accomplished by using random or pseudorandom waveforms. STARK (1968) reported that a pseudorandom waveform composed of a sum of as few as three sinusoids cannot be predicted by human subjects. However, the period of the pseudorandom waveform also seems to be important. If the period is too short, then subjects may be able to recognise and predict certain features of the waveform.

The choice of random or pseudorandom will affect the accuracy of the system identification. For a linear model, the best choice will depend on the linearity of the system. In general, a periodic pseudorandom waveform allows accurate model estimates to be achieved using shorter measurement times; however, if the system has a significant degree of nonlinearity then the use of certain pseudorandom waveforms can lead to bias errors in the linear model estimates (MAKI, 1986). The pseudorandom waveform has a discrete power spectrum, the frequencies being integer multiples of the fundamental frequency (1/period). Nonlinearities will generate harmonics in the response at other frequencies in the input spectrum, thereby creating biased estimates at those frequencies.

This problem may be overcome by using pseudorandom waveforms in which none of the frequencies are small-integer multiples of other frequencies in the signal (MAKI, 1986). Since, in general, only the low harmonics will contain significant energy, this will minimise harmonic distortion at the input frequencies. However, caution should be exercised in using this type of waveform, as the increased spacing between frequencies can cause sharp peaks or troughs in the system frequency response to go undetected.

Pseudorandom waveforms can be generated in a number of forms. Maximum-length binary signals are widely used in system identification applications (GRAUPE, 1976); however, they have the disadvantage that the shape of the power spectrum cannot be changed readily (EYKHOFF, 1974). Greater flexibility is attained by using a signal comprised of a sum of a number of sinusoids with random phase angles. Any desired (discrete) power spectrum can be achieved through appropriate selection of the amplitudes and frequencies of the sinusoids.

### 3.3 *Power spectrum*

The power spectrum specifies the distribution of the perturbation power over the selected frequency range. In general, it is desirable to increase the power at frequencies where the system frequency response is low, to increase the signal-to-noise ratio in the response measurements at those frequencies. Ideally, an optimal input power spectrum could be selected so as to compensate for the system frequency response, yielding an equal signal-to-noise ratio at all frequencies in the measured response. In practice, however, this can only be achieved using an iterative approach, since optimal input design requires *a priori* information about the system characteristics.

### 3.4 *Bandwidth*

The frequency content of the perturbation signal must allow for persistent excitation, i.e. it must exercise the posture-control system over its frequency response limits. Some information about the frequency response limits of the posture-control system can be derived from previous studies. Typically, results show a decrease in gain with increasing frequency. For example, data from ISHIDA and IMAI (1980) show attenuation of approximately 20 to 40 dB as the frequency increases from 0·2 Hz to 2·0 Hz.

Another consideration is subject tolerance. In particular, exposure to high-frequency vibration can lead to discomfort and fatigue. The poorest tolerance is generally in the range from 4 to 8 Hz (MCCORMICK, 1976).

3.5 *Amplitude*

Selection of the perturbation amplitude is governed by three considerations:

(*a*) signal-to-noise ratio in the measurements of the input and output
(*b*) linearity of the model
(*c*) subject safety and tolerance.

The need to measure signals accurately in the presence of measurement noise calls for large input amplitudes, whereas safety and tolerance concerns require small amplitudes. Linear modelling is best served by moderate amplitudes. If the amplitude is too small, then certain sensory components may not be stimulated due to threshold effects. Alternatively, if the amplitude is too large, then large-amplitude nonlinearities may be excited (e.g. muscle strength and range-of-motion limits). In general, a linear model will only apply over a limited range of perturbation amplitudes.

3.6 *Duration*

To minimise random error in the model estimates the measurement time must be maximised. However, in a practical experiment, the measurement time will be limited by subject fatigue and tolerance.

## 4 Experimental methods

Experimental results were obtained using an anterior-posterior translational platform acceleration as the test perturbation and a linear nonparametric transfer function (or frequency-response) model of the posture-control system. The platform acceleration is the input to the system and the centre-of-pressure displacement (for each foot, separately) is the output.

4.1 *Apparatus*

The sway platform allows one degree of freedom of horizontal translational motion. The range of motion is approximately 0·6 m, with a peak speed of 2 m s$^{-1}$ and a peak acceleration of 20 m s$^{-2}$ (for a 100 kg load). The frequency response (carrying a 100 kg load) is flat to within 1 dB for frequencies up to 5 Hz.

For safety, the platform mechanics are covered by a plywood base and safety handrails are mounted onto the undercarriage. The safety handrails also provide a framework for a polyurethane-foam padded enclosure and for a styrofoam visual surround which moves with the platform.

Two force plates are mounted side by side on the platform, one for each foot. For each force plate, four cantilever load cells measure the vertical force and an additional load cell measures the anterior-posterior horizontal force. Ball transfers are placed between the plates and the load cells to minimise crosstalk between the horizontal and vertical force measurements. Based on dynamic tests, the mean absolute error in centre-of-pressure measurement ranged from 0·0 mm to 1·4 mm. The error standard deviation ranged from 0·3 mm to 1·2 mm.

The acceleration of the platform is measured by an accelerometer. Performance tests at accelerations ranging from 0·1 to 5 m s$^{-2}$ resulted in a mean error of 0·07 m s$^{-2}$. The error standard deviation was 0·23 m s$^{-2}$.

The transducer signals are passed from the platform via an umbilical cable to a bank of low-pass anti-aliasing filters (cutoff at 6 Hz) and an analogue-to-digital convertor. The data are sampled at 0·06 s intervals (sampling rate 16·7 Hz) and stored on magnetic disk for later analysis.

4.2 *Subjects*

The eight subjects (four males and four females) who participated in the experiments were all healthy, normal adults with no obvious neurological or musculoskeletal deficits. The subjects ranged in age from 19 to 40.

4.3 *Test procedure*

For each test, the subject was instructed to stand relaxed, with feet comfortably spaced and arms at sides, and to look straight ahead. Headphones were used to listen to music so as to mask any auditory cues from the motor and to distract the subject from consciously modifying his/her motion. Prior to the first test the outlines of the feet were traced, to allow the feet to be repositioned identically in subsequent tests.

Tests were approximately 5 min in duration. The platform motion was controlled to start and end gradually, with no sudden changes in acceleration. During the test the subject was observed to determine whether he/she needed to grab the handrail or move his/her feet in order to maintain balance. At the end of each test the subject was allowed a 2–3 min seated rest. The maximum duration of any single testing session was $1\frac{1}{2}$ hours.

4.4 *Protocol*

Six subjects were each tested using three different waveforms:

(*a*) a pseudorandom input composed of a sum of harmonic sinusoids (HPRN)
(*b*) a pseudorandom input composed of a sum of non-harmonic sinusoids (NHPRN)
(*c*) a Gaussian band-limited white noise random input (RAN).

To construct the random waveform, Gaussian white noise was bandpass filtered with cutoffs at 0·1 and 5·0 Hz. The two pseudorandom signals both had periods of 15·36 s, and were constructed as a sum of equal-amplitude sinusoids having random phase angles uniformly distributed between 0 and 360°. The frequencies of the sinusoids ranged from 0·13 to 4·95 Hz. The HPRN signal comprised 75 sinusoids, spaced at equal frequency intervals of 0·065 Hz. The NHPRN version comprised 15 sinusoids at the following frequencies: 2, 3, 5, 8, 11, 14, 18, 21, 25, 29, 35, 43, 51, 61 and 76 cycles per 15·36 s period.

Three subjects were each tested using three different input power spectra:

(*a*) flat acceleration power spectrum (ACC)
(*b*) flat velocity power spectrum (VEL)
(*c*) flat position power spectrum (POS).

All three signals used a random waveform and had an identical frequency range (0·1–5·0 Hz). For each spectrum the amplitude was adjusted to the upper limit of the subject's tolerance, i.e. the highest amplitude at which the subject could balance without grabbing a handrail or moving his or her feet.

Three subjects were tested at different amplitudes using the NHPRN waveform. Each subject was tested three times at each of five amplitudes, in random order. The largest amplitude tested was the maximum that the subjects could tolerate without moving their feet or grabbing a handrail.

4.5 *Analysis*

The sampled load cell voltages were used to calculate the anterior-posterior locations of the centre of pressure for each foot, and the sampled accelerometer voltages were converted into acceleration values. Treating the acceleration data as the system input and the centre-of-pressure data as the output, the data were fit with a nonparametric linear transfer function model.

The method of 'averaging periodograms' was used (BENDAT and PIERSOL, 1971). First, the data were divided into segments of equal length, discarding the first segment to eliminate any transient response. Then, for each segment, the input/output cross-spectrum, the input autospectrum and the output autospectrum were estimated. These spectral estimates were averaged, and the frequency response was estimated as the ratio of the average cross-spectrum divided by the average input autospectrum. The coherence function was estimated as the squared magnitude of the average cross-spectrum divided by the product of the input and output autospectra.

The spectral estimates were made using a fast Fourier transform (FFT) algorithm. The FFT length was chosen to be 256 points, resulting in a segment duration of 15·36 s and a spectral resolution of 0·065 Hz. Using 50 per cent overlap of segments a total of 37 segments was obtained. In tests using random inputs, the data in each segment were windowed (using a Hamming window) to reduce truncation effects ('leakage'). This was not necessary for the pseudorandom inputs. Since the segment length was chosen to equal the period of these inputs (15·36 s), leakage could not occur.

## 5 Experimental results and discussion

### 5.1 *Waveform*

It is tempting to compare results obtained using different waveforms on the basis of the coherence function, as the coherence is supposed to indicate the 'goodness of fit' of a noise-free, linear, single-input/single-output model. However, this interpretation of the coherence function applies only to RAN inputs (MAKI, 1986). For NHPRN inputs, reduction in coherence indicates measurement noise and/or response due to unmeasured inputs, but cannot be used to assess the linearity of the true system. For HPRN inputs the coherence cannot be interpreted in a useful way.

Typical results are shown in Fig. 1. The large frequency-to-frequency fluctuations in the HPRN frequency response estimate are actually bias errors caused by nonlinear harmonic generation. The RAN estimate is smoother, but still exhibits greater variability than the NHPRN estimate. The larger variance is due in part to nonlinear harmonic generation and in part to the randomness inherent in the RAN input. The lower coherence of the RAN estimate compared with the NHPRN estimate indicates that the RAN linear model estimate has been degraded as a result of nonlinearities in the system. The frequency response derived using the RAN input exhibits no sharp peaks or troughs; therefore, the reduced frequency resolution of the NHPRN input is not a problem.

### 5.2 *Power spectrum*

Fig. 2 shows an example of the input power spectrum and the resulting frequency response and coherence estimates obtained using the ACC, VEL and POS input power spectra.

Because the input was random, the coherence function indicates the relative 'goodness of fit' of a noise-free, linear, single-input/single-output model. As illustrated in the figure, the VEL spectrum resulted in markedly reduced coherence at lower frequencies, with relatively little improvement at the high frequency end, compared with the ACC spectrum. Although the POS spectrum yielded high coherence at frequencies above 4 Hz, the coherence was extremely poor at frequencies below 2 Hz. Compared with the ACC spectrum, the VEL and POS spectra were perceived to be very uncomfortable.

### 5.3 *Bandwidth*

The frequency range used in the experimental tests was approximately 0·1–5·0 Hz. As is evident in Fig. 1, the lower frequency limit was sufficiently small to allow the flat low-frequency asymptote of the frequency response to be determined. At the high-frequency limit there was sufficient additional attenuation (−40 dB) to define a high-frequency asymptote.

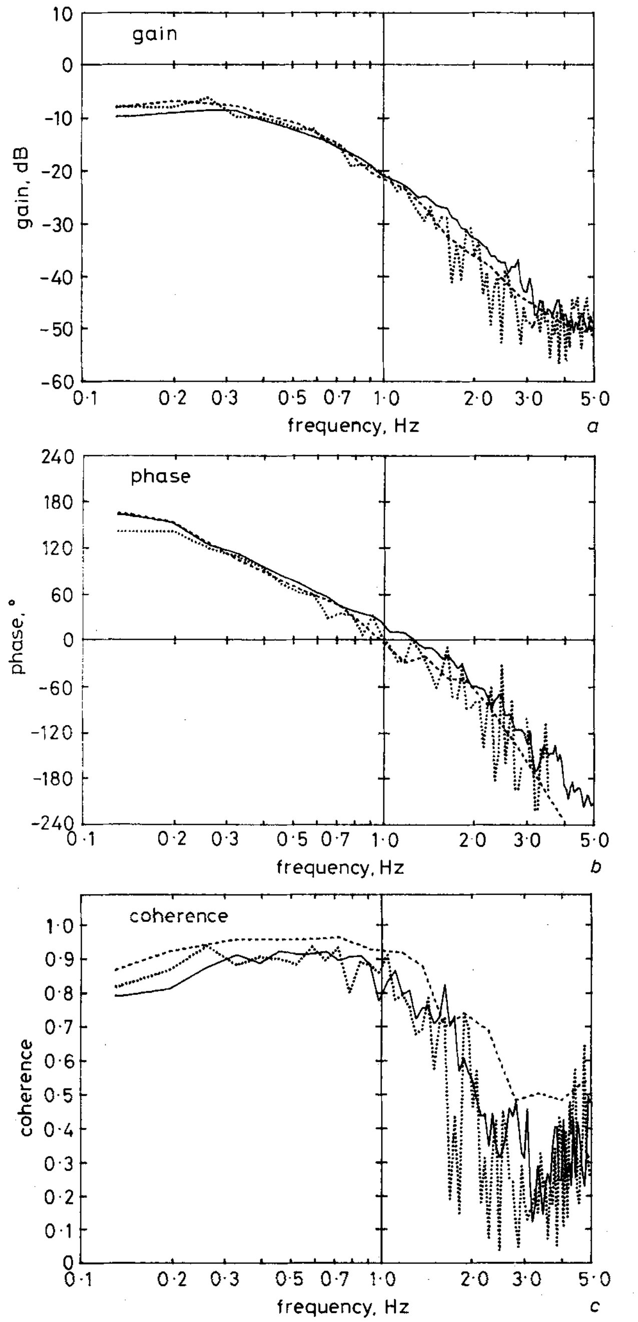


**Fig. 1** *Comparison of waveforms: solid line = random (RAN), dotted line = harmonic pseudorandom (HPRN), broken line = nonharmonic pseudorandom (NHPRN). (a) Frequency response gain, (b) frequency response phase, (c) coherence*

### 5.4 *Amplitude*

Typical results are shown in Fig. 3. Above a certain amplitude, substantial changes in the frequency response (as quantified by gain values at 0·13 Hz) and improvements in mean coherence occurred; however, there was relatively little change as the amplitude was increased further. In general, the best amplitude will depend on the waveform and its frequency content. For the NHPRN waveform tested here, a root-mean square (RMS) amplitude between 0·15 and 0·25 m s$^{-2}$ would be selected for use in subsequent experiments.

### 5.5 *Duration*

The experimental studies used a test duration of approximately 5 min. All eight subjects tested were able to tolerate this duration. Moreover, this duration was sufficient to achieve reasonably accurate results. In the experimental analysis the 5 min of data were divided into 19 segments of 15·36 s duration. Using 50 per cent overlap of adjacent segments, a total of 37 segments was obtained. According to formulae derived for nonparametric frequency response estimates and random Gaussian inputs (DOEBELIN, 1980), averaging over 37 segments of data will yield gain estimates accurate to within 10 per cent with 95 per cent probability, assuming a coherence of 0·8 or greater.

For pseudorandom inputs the required duration will be less. Using a random input, much of the variance in the frequency response estimates is due to the inherent variability in the input signal. For a deterministic pseudorandom input the variance is much less (due only to random noise) and therefore can be reduced to an acceptable level by averaging a smaller number of data segments.

Lacking a general method for estimating the required duration for pseudorandom inputs, the effects of changes in duration were observed experimentally. Frequency-response estimates were made using all 5 min of the data, the first 50 per cent of the data and the first 25 per cent of the data. As illustrated in Fig. 4, reduction to 50 per cent resulted in only small changes in the estimates (maximum change in gain <2 dB, maximum change in phase angle <10°), whereas reduction to 25 per cent resulted in substantially larger changes.

To assess whether the 5 min duration was too long and thereby causing changes in the system characteristics (due to fatigue or adaptation) each test was analysed for stationarity. The output data were divided into 19 15·36 s segments, the variance of each segment was calculated and a 'runs test' (BENDAT and PIERSOL, 1971) was performed. The data for the RAN input showed significant nonstationarity (at $p < 0{\cdot}05$) in only one of 30 tests. The HPRN and NHPRN inputs did not result in any tests with significant nonstationarity.

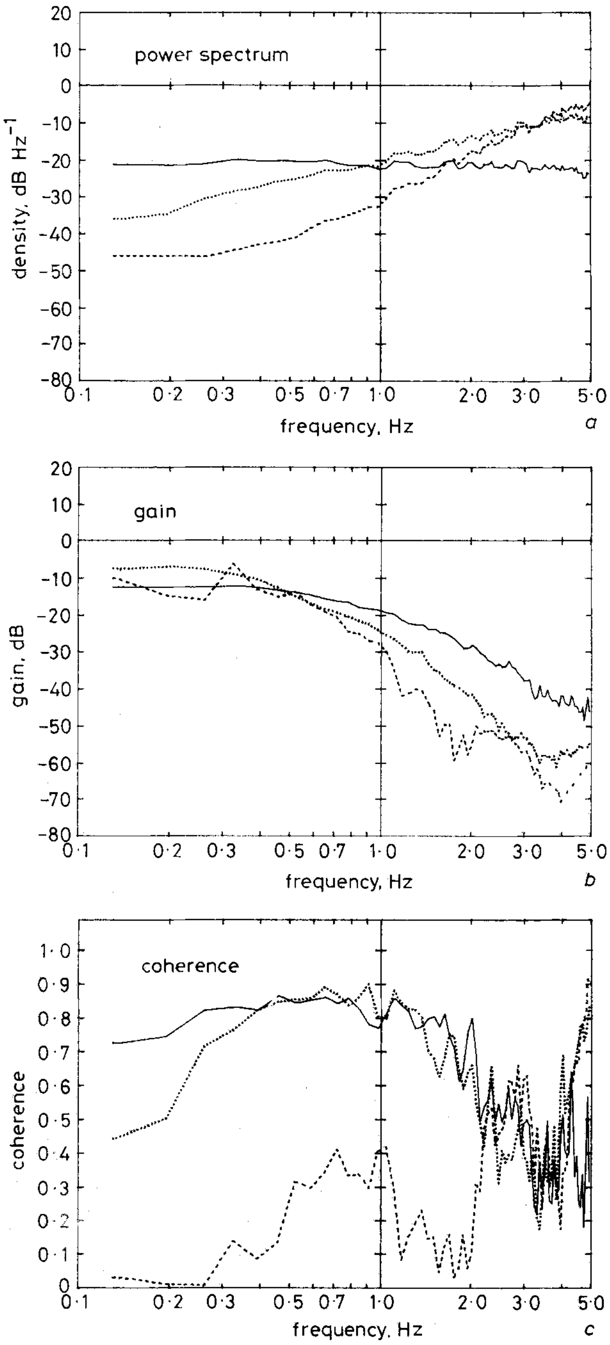


**Fig. 2** *Comparison of power spectra: solid line = flat acceleration (ACC), dotted line = flat velocity (VEL), broken line = flat position (POS). (a) Input power spectra (in terms of acceleration), (b) frequency response gain, (c) coherence*

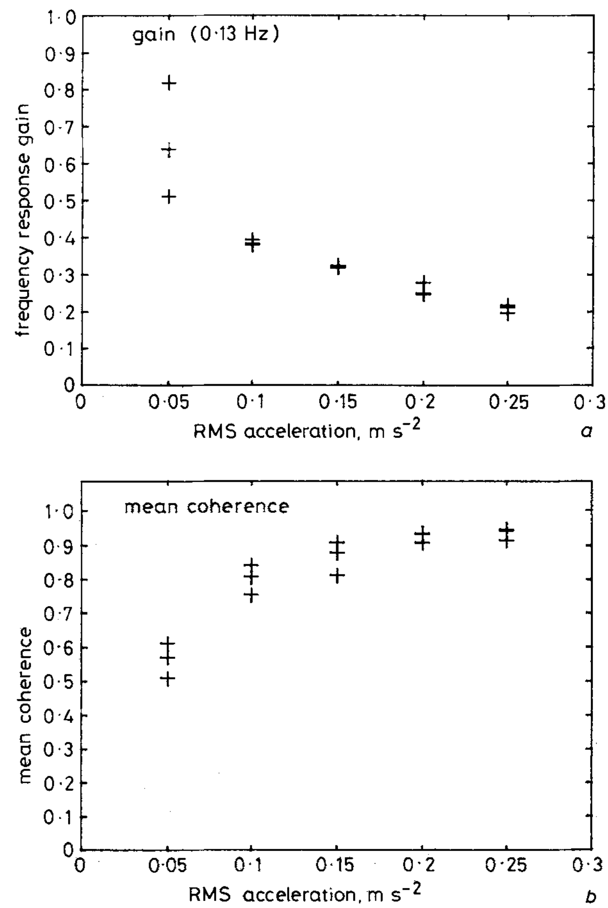


**Fig. 3** *Effects of input amplitude: (a) frequency response gain at 0·13 Hz, (b) mean coherence*

## 6 Conclusion

A translational platform acceleration in the anterior-posterior direction is a reasonable simulation of the kinematics and sensory input of a slip, trip or mis-step. If the platform motion is random or pseudorandom, then the steady-state characteristics of the posture-control system can be identified safely and with minimal subject apprehension. The steady-state model can then be used to attempt to predict transient response to a slip, trip or mis-step.

A pseudorandom perturbation (composed of a sum of nonharmonic sinusoids) will yield more accurate identification of a linear nonparametric transfer function model compared with random signals or pseudorandom signals with harmonic content. Good experimental results are achieved using a flat acceleration power spectrum, with a bandwidth of 0·1–5·0 Hz. The optimal amplitude will depend on the waveform. In general, the best amplitude is a moderate value, large enough to exceed sensory thresholds and to yield adequate signal-to-noise in the measurements yet small enough to guarantee subject safety and to avoid saturation nonlinearities. Using a random input, a test duration of 5 min yields accurate results but is not so long as to cause adaptive or fatigue-related nonstationarity. For pseudorandom inputs reduction of the duration to 2·5 min does not appear to substantially change the results.

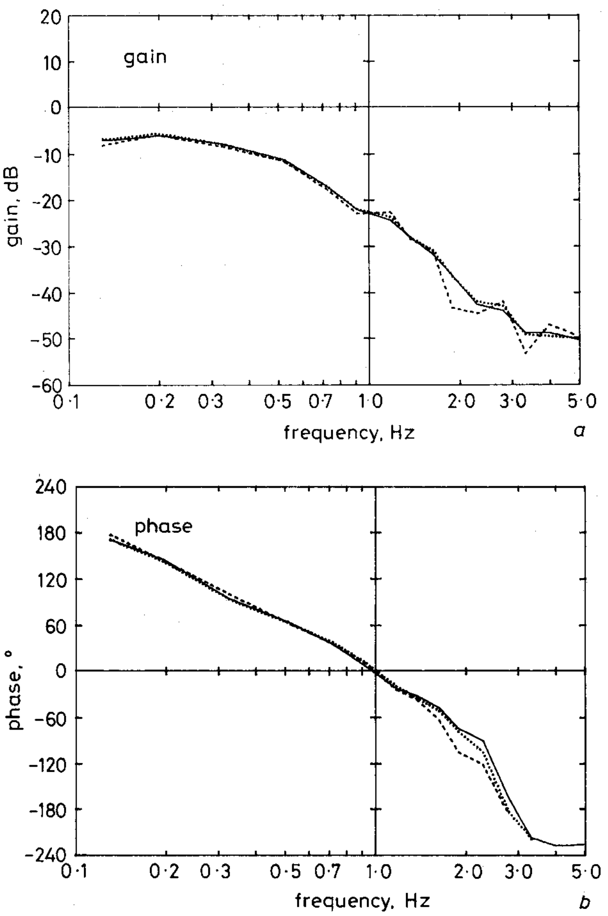


**Fig. 4** *Effect of changes in duration (NHPRN input): solid line = 5 min, dotted line = 2·5 min, broken line = 1·25 min. (a) Frequency response gain, (b) frequency response phase*

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## References

ALLUM, J. H. H. and BUDINGEN, H. J. (1979) Coupled stretch reflexes in ankle muscles: an evaluation of the contributions of active muscle mechanisms to human posture stability. *Progr. Brain Res.*, **50,** 185–195.

ANDERSON, J. H., SOECHTING, J. F. and TERZUOLO, C. (1977) Dynamic relations between natural vestibular inputs and activity of forelimb extensor muscles in the decerebrate cat. 1. Motor output during sinusoidal linear accelerations. *Brain Res.*, **120,** 1–15.

ANDRES, R. O. and ANDERSON, D. J. (1980) Designing a better postural measurement system. *Am. J. Otol.*, **1,** 197–206.

ANDRES, R. O. (1982) Diagnostic implications of induced body sway. In *Nystagmus and vertigo*, TOWE, A. L. and LUSHEI, E. S. (Eds.), Academic Press, New York, 191–204.

BENDAT, J. S. and PIERSOL, A. G. (1971) *Random data: analysis and measurement procedures.* Wiley-Interscience, New York.

BOX, G. E. P. and JENKINS, G. M. (1976) *Time series analysis: forecasting and control.* Holden-Day, San Francisco.

DIENER, H. C., DICHGANS, J., BOOTZ, F. and BACHER, M. (1984) Early stabilization of human posture after a sudden disturbance: influence of rate and amplitude of displacement. *Exp. Brain Res.*, **56,** 126–134.

DOEBELIN, E. O. (1980) *System modelling and response: theoretical and experimental approaches.* John Wiley & Sons, New York.

EYKHOFF, P. (1974) *System identification: parameter and state estimation.* John Wiley & Sons, London.

GANTCHEV, G., DUNVEV, S. and DRAGANOVA, N. (1972) On the problem of the induced oscillations of the body. *Agressologie*, **13B,** 51–55.

GANTCHEV, G. and POPOV, V. (1973) Quantitative evaluation of induced body oscillations in man. *Ibid.*, **14C,** 91–93.

GOODWIN, G. C. and PAYNE, R. L. (1977) *Dynamic system identification.* Academic Press, New York.

GRAUPE, D. (1976) *Identification of systems.* Van Nostrand Reinhold, New York.

GURFINKEL, V. S., LIPSHITS, M. I., MORI, S. and POPOV, K. Y. (1976) The state of stretch reflex during quiet standing in man. *Progr. Brain Res.*, **44,** 473–486.

HIBINO, R. (1980) The role of tonic stretch reflex during standing in man. *Nagoya J. Med. Sci.*, **43,** 15–24.

HONJO, S. and FURUKAWA, R. (1957) The goniometer test. *Ann. Otol. Rhinol. Laryngol.*, **66,** 440–458.

ISERMANN, R. (1980) Practical aspects of process identification. *Automatica*, **16,** 575–587.

ISHIDA, A. and IMAI, S. (1980) Responses of the posture-control system to pseudorandom acceleration disturbances. *Med. & Biol. Eng. & Comput.*, **18,** 433–438.

LITVINTSEV, A. I. (1973) Mechanisms of man's vertical posture control. *Agressologie*, **14B,** 17–21.

MAKI, B. E. (1986) Interpretation of the coherence function when using pseudorandom inputs to identify non-linear systems. *IEEE Trans.*, **BME-33,** (in press).

MCCORMICK, E. J. (1976) *Human factors in engineering and design.* McGraw-Hill, New York.

MEYER, M. and BLUM, E. (1978) Quantitative analysis of postural reactions to induced body oscillations. *Agressologie*, **19A,** 30–31.

NASHNER, L. M. (1971) A model describing vestibular detection of body sway motion. *Acta Otolaryng.*, **72,** 429–436.

NASHNER, L. M. (1976) Adapting reflexes controlling the human posture. *Exp. Brain Res.*, **26,** 59–72.

NASHNER, L. M. (1977) Fixed patterns of rapid postural responses among leg muscles during stance. *Ibid.*, **30,** 13–24.

NASHNER, L. M., WOOLLACOTT, M. and TUMA, G. (1979) Organization of rapid responses to postural and locomotor-like perturbations of standing man. *Ibid.*, **36,** 463–476.

NASHNER, L. M. (1980) Balance adjustments of humans perturbed while walking. *J. Neurophysiol.*, **44,** 650–664.

NASHNER, L. M. and CORDO, P. J. (1981) Relation of automatic postural responses and reaction-time voluntary movements of human leg muscles. *Exp. Brain Res.*, **43**, 395–405.

RAKE, H. (1980) Step response and frequency response methods. *Automatica*, **16**, 519–526.

STARK, L. (1968) *Neurological control systems.* Plenum Press, New York.

TEREKHOV, Y. (1976) Stabilometry and some aspects of its applications: a review. *Biomed. Eng.*, **11**, 12–15.

TOKITA, T., MIYATE, H. and FUJIWARA, H. (1984) Postural response induced by horizontal sway of a platform. *Acta Otolaryngol. Suppl.*, **406**, 120–124.

WALSH, E. G. (1973) Standing man, slow rhythmic tilting, importance of vision. *Agressologie*, **14C**, 79–85.

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