激を与える実験では静的バランス検査で評価できない項目も含まれると考えられ，今後はStep-Acc以外に対しても詳細な解析を検討する必要がある．

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Analysis of body responses to an accelerating platform by the largest-Lyapunov-exponent method

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Abstract: Various disciplines have benefited from the advent of high-performance computing in achieving practical solutions to their problems, and the area of health care is no exception to this. Non-linear signal-processing tools have been developed to understand the hidden complexity of the time series, and these will help clinicians in diagnosis and treatment. Postural study helps the elderly and people with a balancing problem due to various pathological conditions. In elderly subjects, falls are common and may result in injury. Correct postural balance is basic to well-being and it influences our daily life significantly.

These postural signals are non-stationary; they may appear to be random in the time scale and it is difficult to observe the subtle changes for the human observer. Hence, more hidden information can be obtained from the signal using non-linear parameters.

In this paper, ten young normal subjects are subjected to the balancing platform whose acceleration is gradually increased from $1\,\mathrm{m/s^2}$ to $5\,\mathrm{m/s^2}$ to study the postural response. The ankle front–back acceleration and ankle pitch angular velocity sensor data were studied using the largest Lyapunov exponent (LLE). The results show that for higher acceleration of the platform the ankle movement follows a particular rhythm, resulting in a lower Lyapunov exponent. During lower acceleration of the balancing platform, this value is higher because of the random movement of the ankle. In this work, the pattern of the body response was studied using LLE values for different accelerations using ankle data as the base signal for the normal subjects.

Keywords: Lyapunov exponent, sensor, knee, ankle, balance, acceleration, posture

1 INTRODUCTION

Balance aligns the bones with gravity so that the muscles can be in maximum relaxation. Studies indicate that 80 per cent of people in the USA suffer from some form of postural problems (causing back pain) in their lifetimes. This is in sharp contrast with some other cultures around the world, where back pain is present in less than 5 per cent of the population [**1**]. Balance is a state of equilibrium. An out-of-balance situation disturbs the mind in subtle ways. Correct posture is directly related to a relaxed aware ideal state of mind. Every movement that is made, from walking to diving, changes the centre of gravity. The muscles exert force to re-establish equilibrium.

The maintenance of balance is a complex physiological process involving the interaction of many body subsystems. Neuromuscular and musculoskeletal subsystems are important for control of the body position and motor output. Sensory system components coordinate the information regarding the body's position relative to gravity, environment, and positions of body parts in relation to each other.

The importance of the biosignal analysis, which exhibits typical complex dynamics, has been recognized in the field of non-linear dynamics. Several non-linear parameters have been proposed to detect the hidden important dynamic properties of the physiological phenomenon. These techniques are

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based on the concept of chaos, which has been applied to many areas including the areas of biomedical informatics. The theory of chaos has been applied to the postural signals to study the postural sway [2]. Efforts have been made to determine non-linear parameters in rehabilitation, and it has been shown that they are useful indicators of pathologies. Cavanaugh *et al.* [3] have used the approximate entropy to detect changes in postural control during quiet standing in athletes with normal postural stability after cerebral concussion effectively. Kinematic sensors, accelerometers, and gyroscopes help to monitor the long-term physiological signals related to the postural study [4, 5]. Postural balance was measured with the help of a force platform system in four test conditions: normal standing with eyes open and closed (both for 30 s), semitandem (20 s), and tandem stand with eyes open (20 s) [6]. The results of the study indicate that the deterioration in balance function starts at a young age and worsens further from about 60 years onwards.

Body sway in a standing position with both legs for 30 s, and for 10 s during one-leg standing with eyes open or closed alternating between left and right legs (five times each), were studied using a stabilimeter [7]. The results indicate that the lower extremity muscle power did not appear to be the dominant factor in maintaining balance in these young subjects. Recently, Stel *et al.* [8] have shown that significant difference between the balance performances of older fallers and non-fallers indicate that poor balance abilities are found in fallers. Different balance tests (clinical and laboratory) have been studied to predict the postural stability in community-dwelling older subjects [9].

Methods of non-linear dynamics, namely the Lyapunov exponent, correlation dimension, and approximate entropy, were used to analyse centre-of-pressure (COP) data during different sitting postures [10]. Variability in human movement data can be analysed by a linear method using power spectral analysis and the non-linear method [11]. The nature of variability present in time series generated from gait parameters of two different age groups, namely the elderly and young females, was studied using non-linear analysis [12]. The elderly exhibited significantly larger Lyapunov exponents and correlation dimensions for all parameters evaluated, indicating local instability. The linear measures also indicated that the elderly demonstrated significantly higher variability.

Both the methods, i.e. stabilogram diffusion analysis and detrended fluctuation analysis (DFA), were able to identify differences between the postural stabilities of control and elderly subjects for time series as short as 5 s [13]. In addition, measurements proved to be reliable across testing sessions, with DFA the more robust method for anteroposterior (AP) displacement. The non-linear behaviours of the postural signals in young and elderly normal subjects were analysed by fractal dimension analysis using COP signals [14].

The largest Lyapunov exponent (LLE) was estimated to quantify the chaotic behaviour of postural sway. COP data and AP displacements (stabilogram) were obtained by static posturography tests performed on control subjects [2, 15]. LLE values were found to be positive, although close to zero. This suggests that postural sway derives from a process exhibiting weakly chaotic dynamics.

Recently, Han *et al.* [16] have used the COP trajectories, Rényi dimension, and sway path to classify the normal and balance disorder groups in quiet stance. The COP was obtained using a force-sensing mat. The complexities of centre-of-mass (COM) and COP displacements in healthy elderly subjects were analysed using fractal dimension analysis [17]. The subjects performed the test with eyes open and closed. The COP was measured using a force platform while the COM was derived from markers placed on the body using the Yeadon–Morlock 14-segment human model.

In the above studies, the subjects stood on a non-moving platform. However, in the real-world situation, people may be standing on a moving vehicle. In this work, attempts were made to simulate this situation using an accelerating platform.

Displacements of ankle data were analysed because they fall into three distinct categories, namely angle, hip, and step strategies; hence they would be expected to give more varied results.

The objective of this project focused on improving the quality of life for elderly subjects. One area contributing to the quality of life is the ability to perform daily activities including the use of public transport. It is the intention to pursue these studies in this direction in the next phase.

2 METHODOLOGY

In this project, normal subjects stood on a motorized horizontal platform. The platform was then accelerated in the posterior direction, continued to move for a short interval at constant speed, and then decelerated to rest. Accelerometers and rate gyroscopes attached to points on the body, and foot pressure sensors were used to record the subjects' res-

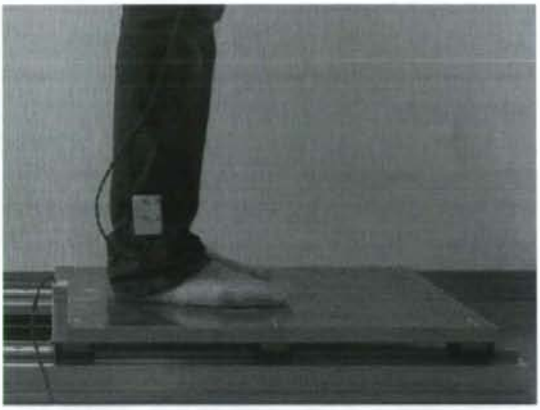

Fig. 1 General layout of the equipment

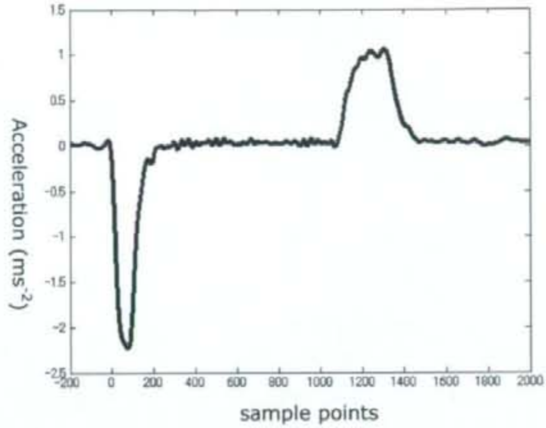

Fig. 2 Acceleration of the platform

ponse. During each trial, the subject's initial posture was checked to ensure that it was in accordance to the standard posture. Then a signal was given to the subject that the platform was about to move. Within a delay time of 1–10 s after the signal, the platform moved. After the platform had stopped moving, the initial posture and conditions were then resumed and checked again before repeating the experiment with different magnitudes of acceleration and delays after the signal. The magnitude of acceleration and delay were randomly applied and do not follow any sequence. Figure 1 shows the layout of the equipment used for this work.

2.1 The platform

The platform (Fig. 1) was controlled by a programmable logic controller (Keyence MV-1000) via a servo amplifier (Keyence MV-41). The movement of the platform was as follows.

1. The platform accelerated in the posterior direction for a fixed duration of 100 ms.
2. The magnitude of posterior acceleration varies from 0.2 m/s^2 to 5.0 m/s^2, randomly executed.
3. After the posterior acceleration, the platform continued to move at a constant speed for a fixed duration of 1000 ms.
4. After the constant-speed movement, the platform was decelerated to a stop at a constant magnitude of 1.0 m/s^2.

2.2 Posture and sensors

The initial posture was standing upright with arms folded and eyes open. Three-axis accelerometer and three-axis rate gyro modules (Gyrocube O-Navi 23505) were attached to the ankle of the subject. A similar module was attached to the platform to measure its acceleration. The sampling rate was 1000 Hz.

2.3 The protocol used

The following measurement protocol was used. There was measurement of all six linear and angular axes of acceleration and angular velocity at the waist, knee, and ankle, and the foot pressure map was also measured. Socks were worn by the subjects. Ten normal male subjects, of age 22.4 ± 2.3 years, participated in the experiment.

The ethics committee of Chiba University has approved the data for this research purpose. Written consent was obtained from each subject before they participated in this experiment.

2.4 State space reconstruction

Analysis of the signal depends on the successful reconstruction of the state space of the underlying process. There are a number of rigorous theorems about the possibility to reconstruct a state space from the signal. The reconstructed attractor from the signal must preserve the invariant characteristics of the original unknown attractor. This is achieved by choosing an appropriate embedding dimension m and delay time τ, in the so-called delay coordinate method. In the analysis an embedding dimension m of 4 and delay τ of 11 were obtained [**18**]. τ was evaluated using the actual mutual information

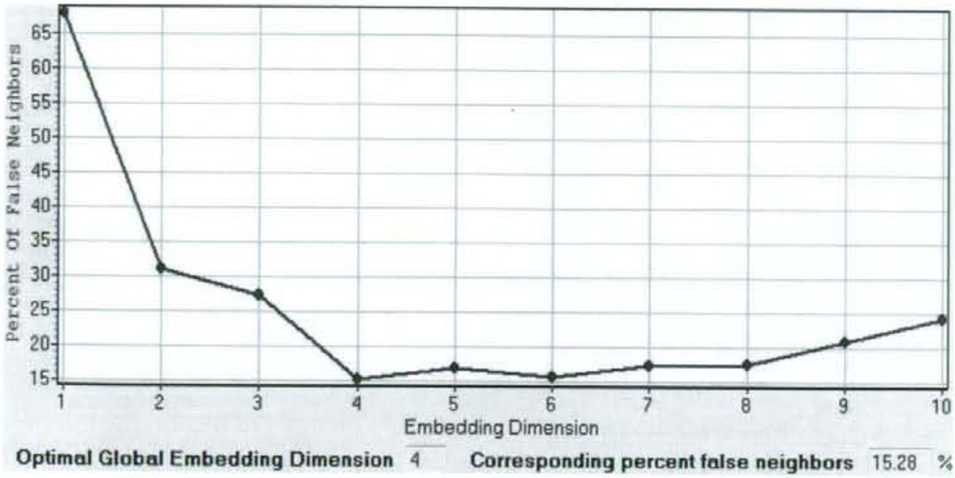

Fig. 3 Estimation of the embedding dimension

method and m using the false nearest-neighbour method. These methods are described below.

2.4.1 Estimation of the embedding dimension m

If the reconstructed attractor is projected to a lower dimension than the original dimension, then certain distant points may appear as false neighbours [**19**]. In a higher dimension these false neighbours may appear as distant points. As the embedding dimension is increased, the false nearest neighbours (FNNs) may vanish or reach some acceptable level. Hence, the FNN method is used to calculate the optimum embedding dimension.

The criterion for evaluating each element $\mathbf{y}_i$ in the time series is to look for its nearest neighbour $\mathbf{y}_j$ in the m-dimensional space and to calculate the distance $\|\mathbf{y}_i - \mathbf{y}_j\|$; D_i is calculated, by increasing i, according to

$$D_i = \frac{\left|\mathbf{y}_{i+1} - \mathbf{y}_{j+1}\right|}{\left\|\mathbf{y}_i - \mathbf{y}_j\right\|} \tag{1}$$

There will be FNNs, if D_i exceeds some threshold value D_t. The criterion which considers that the embedding dimension is sufficiently high is that the number of points verifying that $D_i > D_t$ is zero or at least sufficiently small. The algorithm is sensitive to the choice of D_t. The graph of FNN versus increasing embedding dimension is a monotonically decreasing graph. The optimum embedding dimension usually can be found near the crossing of the 30 per cent threshold. The embedding dimension is the value for which there will be no FNN or a value within the acceptable level. In this case, m was obtained as 4 and D_t was chosen as 11. Figure 3 shows the estimation of the embedding dimension for the data using the FNN method.

2.4.2 Estimation of the delay time τ

A one-to-one embedding can be obtained for any value of the delay time $\tau > 0$ for an infinite amount of noise-free data. However, values of τ that are both too small and too large will cause failures of the reconstruction in the case of the observed finite noisy time series. The optimal τ is determined using the mutual information function $I(\tau)$ [**20**]. The idea is that a good choice for τ is a value that, given the state of the system $x(n)$, provides maximum new information with measurement at $x(n+\tau)$.

The mutual information function evaluated for the present data between two instants n and $n+\tau$ is given by

$$I(\tau) = \sum_{n=1}^{N} P(x(n), x(n+\tau)) \log_2 \left[\frac{P(x(n), x(n+\tau))}{P(x(n)) P(x(n+\tau))} \right] \tag{2}$$

where $P(x(n), x(n+\tau))$ are the probabilities of observing $x(n)$ and $x(n+\tau)$. $P(x(n))$ is the probability of $x(n)$.

$I(\tau)$ becomes zero when $x(n)$ and $x(n+\tau)$ are independent. A graph of $I(\tau)$ versus τ is used to calculate the optimum delay time. $I(\tau)$ is the maximum for $\tau = 0$ as $x(n+0) = x(n)$. As τ is increased, $I(\tau)$ decreases and then increases again. The value of the time

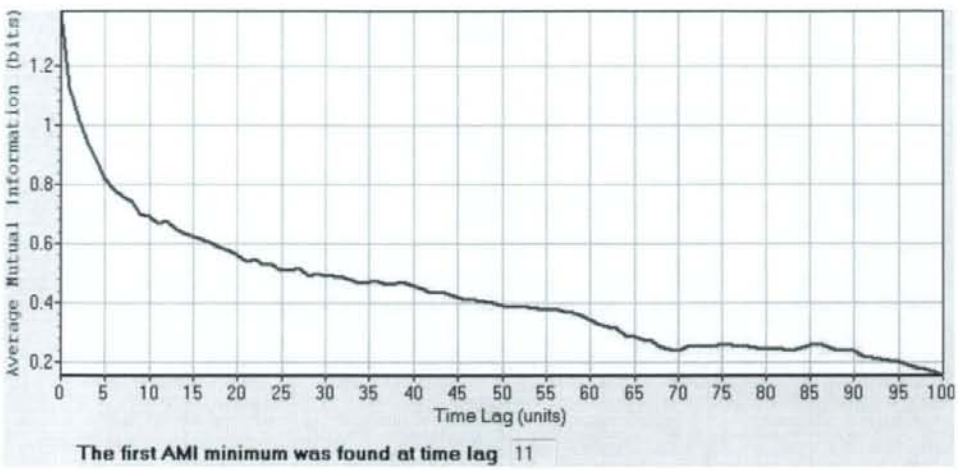

Fig. 4 Estimation of the delay using average mutual information

delay where $I(\tau)$ reaches its first minimum is the optimal τ for use in state space reconstruction [**20**]. The mutual information function for the present data is given in Fig. 4. It can be clearly seen that the mutual information $I(\tau)$ reaches its first minimum at $\tau = 11$. Hence the optimal embedding delay τ_{opt} is determined using the mutual information function in this study. In this work, a time delay of 11 was obtained.

2.5 Largest Lyapunov exponent

The Lyapunov exponent λ is a quantitative measure of the sensitivity to the initial conditions. It indicates the average rate of divergence of two neighbouring trajectories. The time-domain signal is embedded in the phase space and analysed in that space. λ gives the measure of the exponentially fast divergence or convergence of nearby orbits in phase space. Therefore, the existence of a positive λ for almost all initial conditions in a bounded dynamic system is a widely used definition of deterministic chaos. Lyapunov exponents are usually used to distinguish between chaotic dynamics and periodic signals. A negative exponent implies that the orbits approach a common fixed point. A zero exponent means that the orbits maintain their relative positions; they are on a stable attractor. A positive exponent indicates that the orbits are on a chaotic attractor.

The algorithm proposed by Wolf *et al.* [**21**] is used to determine the LLE. For the acceleration data, $x(t)$ for m-dimensional phase space with a delay coordinate τ that is a point on the attractor is given by $\{x(t), x(t+\tau), x(t+2\tau), \ldots, x[t+(m-1)\tau]\}$. The nearest neighbour to the initial point $\{x(t_0), x(t_0+\tau), x(t_0+2\tau), \ldots, x[t_0+(m-1)\tau]\}$ is located. Let $P(t_0)$ be the distance between these two points. At a later time t_1, the initial length will evolve to a length $P'(t_1)$. The mean exponential rate of divergence of two initially close orbits is characterized by

$$\lambda = \frac{1}{t_N - t_0} \sum_{k=1}^{N} \log_2 \left[\frac{P'(t_k)}{P'(t_{k-1})} \right] \tag{3}$$

The maximum positive λ is the LLE. In this work, the total length N of the acceleration data is 2000.

2.6 Surrogate data

The purpose of surrogate data is to test for any nonlinearity in the original data. This concept of surrogate data analysis was introduced by Theiler *et al.* [**22**]. It can be obtained by phase randomizing the original data. The mean, variance, autocorrelation function, and power spectrum are the same as those of the original data, with altered phase component. The random phase spectrum can be obtained by the following methods.

1. *Random phase.* The phase values of the Fourier-transformed signal are chosen randomly.
2. *Phase shuffle.* The phase values of the original spectrum are used in random order.
3. *Data shuffle.* The phase components of the original spectrum are used in random order and the sorted values of the surrogate data are substituted by the corresponding sorted values of the reference sequence additionally.

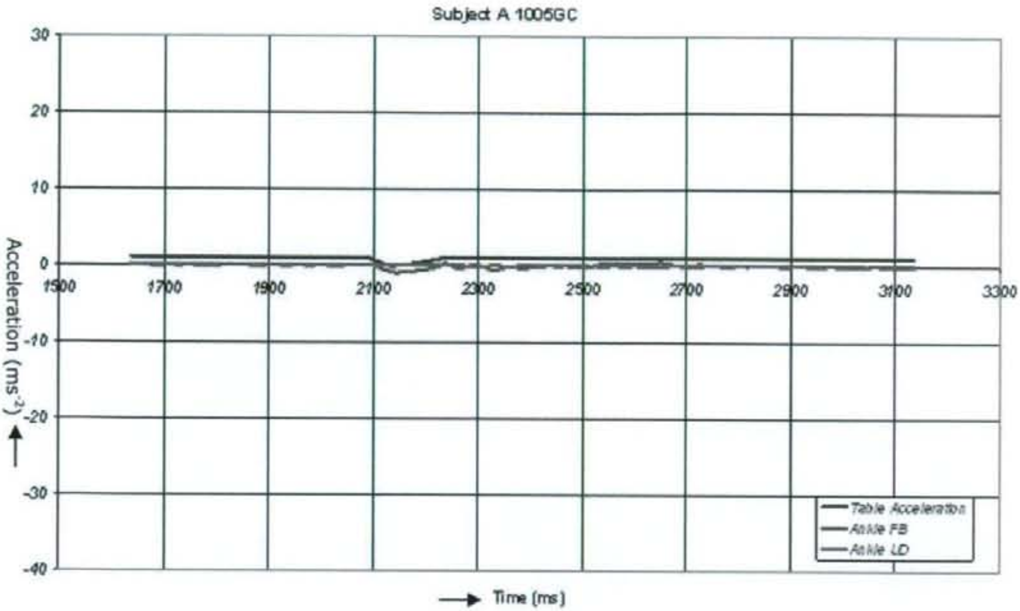

Fig. 5 Typical response, $1.0\,m/s^2$ (FB, front–back; UD, up–down)

Surrogate data were obtained by Fourier decomposition with the same amplitudes as the empirical data decomposition but with random phase components. This was achieved using the chaos data analyser [**23**]. Ten sets of surrogate data are generated for each person. The LLE is obtained for both the original and the surrogate data sets. It was found that the LLE for the surrogate data and that for the original data differ from each other by more than 58 per cent. This rejects the null hypothesis and hence the original data contain non-linear features.

3 RESULTS

The subject's response can generally be classified into three categories: first, no lifting of the soles; second, lifting of the soles; and third, stepping of the feet. Figures 5, 6, and 7 show the responses of a typical subject to acceleration magnitudes of $1.0\,m/s^2$, $4.0\,m/s^2$, and $4.8\,m/s^2$ respectively. Only the acceleration of the ankle in the front–back (dark grey curve) and up–down (light grey curve) directions are shown.

Table 1 shows the results of the LLE for ten subjects for ankle front–back acceleration and ankle pitch rate. Figure 8 shows the graph of Lyapunov exponent versus the acceleration magnitude.

The LLE quantifies the sensitivity of the system to initial conditions and gives a measure of predictability. This value decreases in various ranges with increase in the acceleration speed of the balance platform, indicating that the signal becomes less chaotic for normal subjects. The LLE corresponding to the ankle pitch rate and ankle front–back acceleration decreases with increase in the speed of the balancing platform.

4 DISCUSSION

From the raw data shown in Figs 2, 5, 6, and 7, it is easily apparent that at low acceleration magnitudes, only slight movement of the ankle occurs. During moderate acceleration magnitudes, there is greater ankle movement, and they occur over the entire period when the platform is moving. At high acceleration magnitudes, the ankle movement is very drastic, and it occurs only near the latter half of the platform movement.

Table 1 shows the values of LLE for different acceleration speeds of the balance platform. It was noted that the ankle front–back acceleration shows a clear decrease in the trend for the rise in the acceleration speeds.

The ankle sensor parameters (LLE) decrease as the acceleration magnitude becomes greater, and in-

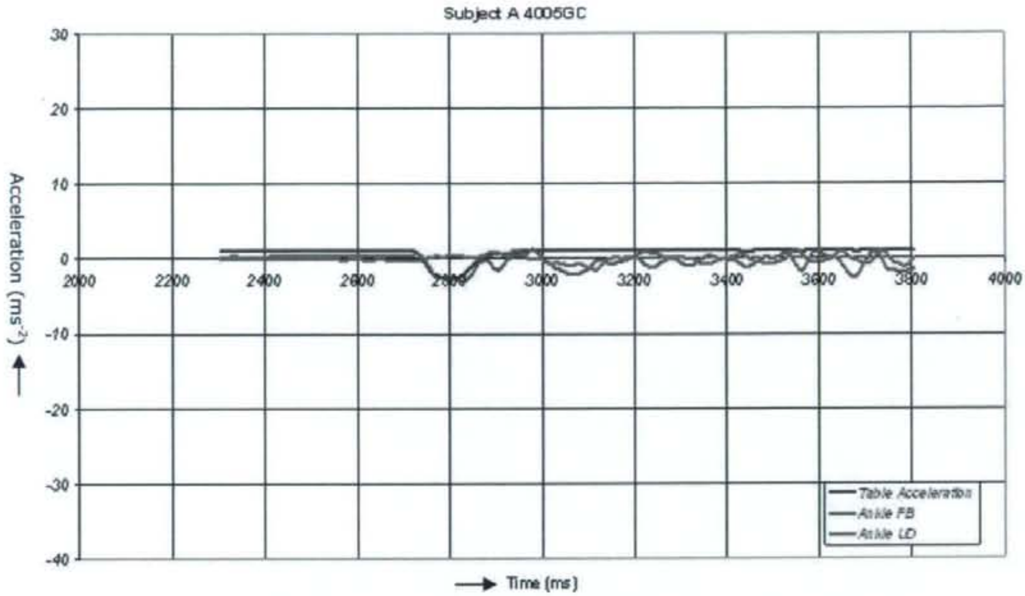

Fig. 6 Typical response, $4.0\,\mathrm{m/s^2}$ (FB, front–back; UD, up–down)

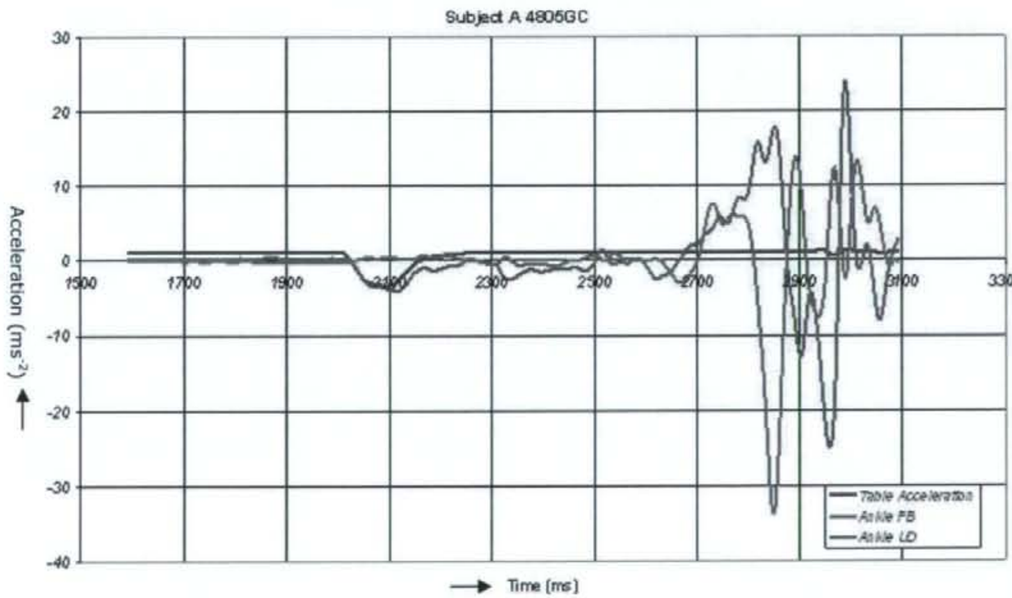

Fig. 7 Typical response, $4.8\,\mathrm{m/s^2}$ (FB, front–back; UD, up–down)

creases slightly when the magnitude is less. This is because, when the magnitude is greater, the ankle moves more quickly in a particular rhythmic fashion. Therefore, these values will be smaller. However, when the acceleration magnitude is low, there is more random movement and hence these values will be slightly higher.

It is hypothesized that the drastic ankle movement (stepping) at high acceleration magnitudes have a hidden pattern and depend on the athletic ability of

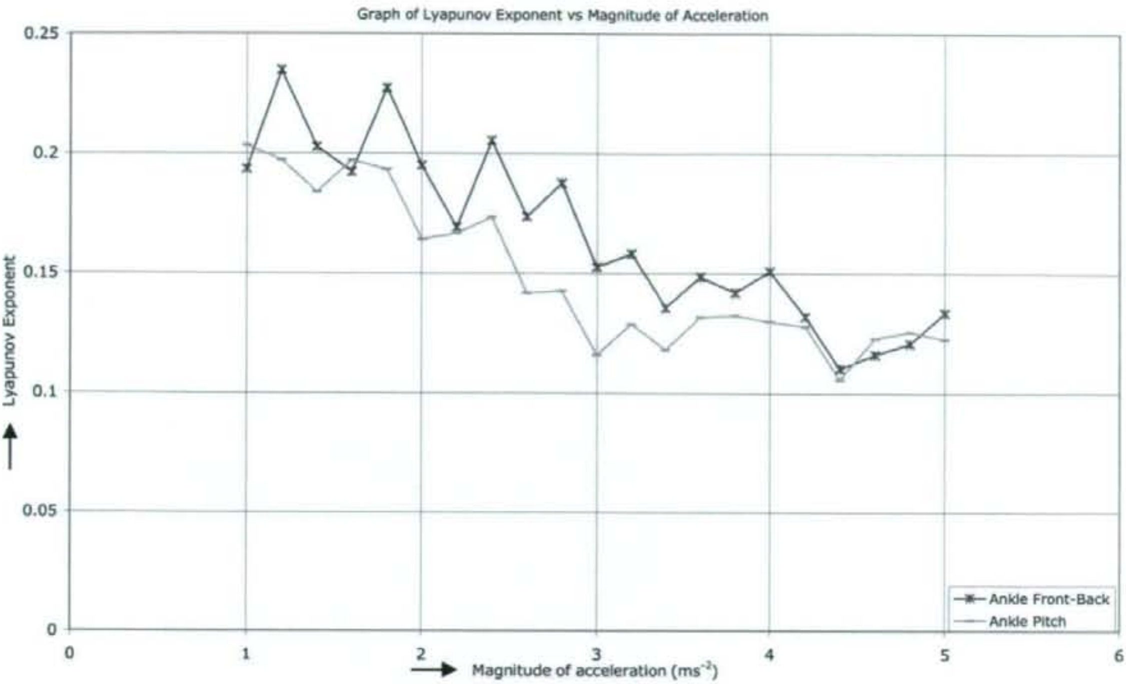

Fig. 8 Graph of the LLE versus the acceleration magnitude

the subject. The reason is that the subject will try to avoid falling as much as possible, exerting maximum effort. Hence the cadence of the stepping will be at the subject's 'favourite' pace.

For low acceleration magnitudes, fluctuations in ankle signals occur immediately after the acceleration. These are more random and hence result in higher LLE values.

The correlation dimension and the LLE studied on a time series of stabilograms showed distinct values in healthy subjects and Parkinsonian subjects [**24**]. Ohtaki *et al.* [**25**] have studied the Lyapunov exponents of young and elderly subjects, and of groups before and after exercise intervention. Experimental results demonstrated that exercise intervention improved the local dynamic stability of walking. During

Table 1 Average LLE of ten subjects for ankle front–back acceleration and ankle pitch angular velocity

Acceleration magnitude (m/s^2)	Ankle front–back acceleration (m/s^2)	Ankle pitch angular velocity (degree/s)
1.0	0.1936 ± 0.001 26	0.2034 ± 0.001 012
1.2	0.2348 ± 0.001 144	0.1974 ± 0.000 684
1.4	0.2028 ± 0.002 954	0.184 ± 0.001 314
1.6	0.1924 ± 0.000 516	0.1972 ± 0.000 104
1.8	0.2274 ± 0.000 665	0.1934 ± 0.000 887
2.0	0.1952 ± 0.000 349	0.1642 ± 0.000 285
2.2	0.1692 ± 0.001 774	0.1668 ± 0.001 184
2.4	0.2056 ± 0.000 572	0.1734 ± 0.000 888
2.6	0.1736 ± 0.000 68	0.1418 ± 0.000 087 2
2.8	0.1878 ± 0.002 233	0.1426 ± 0.003 489
3.0	0.1526 ± 0.003 098	0.116 ± 0.002 078
3.2	0.1582 ± 0.002 545	0.1288 ± 0.000 283
3.4	0.1356 ± 0.004 318	0.118 ± 0.000 918
3.6	0.1484 ± 0.003 514	0.1318 ± 0.001 405
3.8	0.142 ± 0.004 707	0.1324 ± 0.001 019
4.0	0.1508 ± 0.003 807	0.13 ± 0.000 477
4.2	0.132 ± 0.002 526	0.128 ± 0.001 059
4.4	0.1104 ± 0.000 302	0.1058 ± 0.000 846
4.6	0.1162 ± 0.000 898	0.123 ± 0.000 454
4.8	0.1208 ± 0.000 166	0.1256 ± 0.000 254
5.0	0.1336 ± 0.001 243	0.1226 ± 0.000 299

quiet standing, the human body continually moves about in an erratic and possibly chaotic fashion. It has been shown that postural sway is indistinguishable from correlated noise and that it can be modelled as a system of bounded correlated random walks [**26**]. The results suggest that the postural control system incorporates both open-loop and closed-loop control mechanisms.

In this moving-platform experiment, at low acceleration magnitudes, the ankle movements are expected to be random, to maintain balance, and thus to confirm the findings. At high magnitudes, the ankle movements are less variable: first, before stepping occurs, they depend on the 'natural frequency' of the subject leaning back and forth in an oscillatory manner; second, after stepping occurs, they depend on the 'natural frequency' of the lower limbs and muscles, the subjects stepping at their favourite cadences. The present authors intend to continue this work by analysing the cadences of the same subjects on a treadmill to find their most efficient pace.

In this work, the responses of the ankle signal due to the movement of the acceleration platform have been analysed. The concept can be applied to analyse the quality of life of elderly subjects to perform their daily activities including the use of public transport.

5 SUMMARY

This work is focused on the application of a proper non-linear technique to analyse the complexity of postural signals. The surrogate data analysis applied to the data exhibited the deterministic and non-linear nature of the signals. The results of a force platform balance test suggest that the LLE for ankle front–back and ankle pitch rate decreases with increase in the balance platform acceleration. The proposed method was able to quantify the response of ankle signals to the external force (acceleration).

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